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Abstract

Conflict learning algorithms are an important component of modern MIP and CP solvers. But strong conflict information is typically gained by depth-first search. While this is the natural mode for CP solving, it is not for MIP solving. Rapid Learning is a hybrid CP/MIP approach where CP search is applied at the root to learn information to support the remaining MIP solve. This has been demonstrated to be beneficial for binary programs. In this paper, we extend the idea of Rapid Learning to integer programs, where not all variables are restricted to the domain $\{0, 1\}$, and rather than just running a rapid CP search at the root, we will apply it repeatedly at local search nodes within the MIP search tree. To do so efficiently, we present six heuristic criteria to predict the chance for local Rapid Learning to be successful. Our computational experiments indicate that our extended Rapid Learning algorithm significantly speeds up MIP search and is particularly beneficial on highly dual degenerate problems.

1 Introduction

Constraint programming (CP) and integer programming (IP) are two complementary ways of tackling discrete optimization problems. Hybrid combinations of the two approaches have been used for many years, see, e.g., [2, 9, 10, 17, 37, 42, 22]. Both technologies have incorporated *conflict learning* capabilities [21, 27, 38, 1, 35] that derive additional valid constraints from the analysis of infeasible subproblems extending methods developed by the SAT community [33].

Conflict learning is a technique that analyzes infeasible subproblems encountered during a tree search algorithm. In a tree search, each subproblem can be identified by its local variable bounds, i.e., by local bound changes that come from branching decisions and propagation at the current node and its ancestors. If propagation detects infeasibility, conflict learning will traverse this chain of decisions and deductions reversely, reconstructing which bound changes led to which other bound changes. In this way, conflict learning identifies explanations for the infeasibility. If it can be shown that a small subset of the bound changes suffices to prove infeasibility, a so-called conflict constraint is generated that can be exploited in the remainder of the search to prune parts of the tree.

In the context of constraint programming, conflict constraints are also referred to as *no-goods*. For binary programs (BPs), i.e., mixed integer (linear) programs for which all variables have domain $\{0, 1\}$, conflict constraints will have the form of *set covering* constraints. These are linear constraints of the form “sum of variables (or their negated form) is greater than or equal to one”.

Rapid Learning [13] is a heuristic algorithm for BPs that searches for valid conflict constraints, global bound reductions, and primal solutions. It is based on the observation that a CP solver can typically perform an incomplete search on a few thousand nodes in a fraction of the time that a MIP solver needs for processing the root node. In addition, CP solvers make use of depth-first search, as opposed to the hybrid best-first/depth-first search of MIP solvers, which more rapidly generates strong no-goods. Typically CP solvers do not differentiate the root node from other nodes. They apply fast (at least typically) propagation algorithms to infer new information about the possible values variables can take, and then take branching decisions. In contrast, a MIP solver invests a substantial amount of time at the root node to gather global information about the problem and to initialize statistics that can help for the search. A significant portion of root node processing time comes from the computational effort needed to solve the initial LP relaxation from scratch. Further aspects are the LP resolves during cutting plane generation, strong branching [7] for branching statistic evaluation, and primal heuristics, see, e.g., [11].

The idea of Rapid Learning is to apply a fast CP depth-first branch-and-bound search for a few hundred or thousand nodes, generating and collecting valid conflict constraints at the root node of a MIP search. Using this, the MIP solver is already equipped with the valuable information of which bound changes will lead to an infeasibility, and can avoid them by propagating the derived constraints. Just as important, the partial CP search might find primal solutions, thereby acting as a primal heuristic. Furthermore, the knowledge of conflict constraints can be used to initialize branching statistics, just like strong branching. In this paper, we will extend Rapid Learning to integer programs and to nodes beyond the root.

The remainder of the paper is organized as follows. In Section 2, we provide more background on conflict learning for MIPs, in particular the extension to general integer variables, which is important for our extended Rapid Learning algorithm. In Section 3, we describe details of the Rapid Learning algorithm for general integer programs, extending the work of Berthold et al. [13]. In Section 4,

we discuss what special considerations have to be taken when applying Rapid Learning repeatedly at local subproblems during the MIP tree search instead of using it as a onetime global procedure. We introduce six criteria to predict the benefit of local Rapid Learning. Section 5 presents our computational study, in which we apply our extended Rapid Learning algorithm to a set of integer programs from the well-known benchmark sets of MIPLIB 3, MIPLIB 2003, and MIPLIB 2010 [28]. The experiments have been conducted with the constraint integer programming solver SCIP [24] and indicate that a significant speed-up can be achieved for (pure) integer programs, when using Rapid Learning locally. In Section 6, we conclude.

2 Conflict Learning in Integer Programming

A mixed integer program is a mathematical optimization problem defined as follows.

Definition 1 (mixed integer program) *Let $m, n \in \mathbb{Z}_{\geq 0}$. Given a matrix $A \in \mathbb{R}^{m \times n}$, a right-hand-side vector $b \in \mathbb{R}^m$, an objective function vector $c \in \mathbb{R}^n$, a lower and an upper bound vector $l \in (\mathbb{R} \cup \{-\infty\})^n$, $u \in (\mathbb{R} \cup \{+\infty\})^n$ and a subset $\mathcal{I} \subseteq \mathcal{N} = \{1, \dots, n\}$, the corresponding mixed integer program (MIP) is given by*

$$\begin{aligned}
 \min \quad & c^\top x \\
 \text{s.t.} \quad & Ax \leq b \\
 & l_j \leq x_j \leq u_j \quad \text{for all } j \in \mathcal{N} \\
 & x_j \in \mathbb{R} \quad \text{for all } j \in \mathcal{N} \setminus \mathcal{I} \\
 & x_j \in \mathbb{Z} \quad \text{for all } j \in \mathcal{I}.
 \end{aligned} \tag{1}$$

Mixed integer programs can be categorized by the classes of variables that are part of their formulation:

- If $\mathcal{N} = \mathcal{I}$, problem (1) is called a *(pure) integer program (IP)*.
- If $\mathcal{N} = \mathcal{I}$, $l_j = 0, j \in \mathcal{N}$ and $u_j = 1, j \in \mathcal{N}$, problem (1) is called a *(pure) binary program (BP)*.
- If $\mathcal{I} = \emptyset$, problem (1) is called a *linear program (LP)*.

Conflict analysis techniques were originally developed by the artificial intelligence research community [40] and, later extended by the SAT community [33]; they led to a huge increase in the size of problems modern SAT solvers can handle [31, 33, 43]. The most successful SAT learning approaches use so-called *one-level first unique implication point (1-UIP)* [43] learning which in some sense captures the conflict constraint “closest” to the infeasibility. Conflict analysis also is successfully used in the CP community [25, 26, 35] (who typically refer to it as no-good learning) and the MIP world [1, 21, 38, 41]. Nowadays, commercial MIP solvers like FICO Xpress [23] employ conflict learning by default.

Constraint programming and mixed integer programming are two complementary ways of tackling discrete optimization problems. Because they have different strengths and weaknesses hybrid combinations are attractive. One notable example, the software SCIP [3], is based on the idea of *constraint integer programming* (CIP) [2, 6]. CIP is a generalization of MIP that supports the notion of general constraints as in CP. SCIP itself follows the idea of a very low-level integration of CP, SAT, and MIP techniques. All involved algorithms operate on a single search tree and share information and statistics through global storage of, e.g., solutions, variable domains, cuts, conflicts, the LP relaxation and so on. This allows for a very close interaction amongst CP and MIP (and other) techniques.

There is one major difference between BPs and IPs in the context of Rapid Learning: in IP, the problem variables are not necessarily binary. To deal with this, the concept of a *conflict graph* needs to be extended. A conflict graph gets constructed whenever infeasibility is detected in a local search node; it represents the logic of how the set of branching decisions led to the detection of infeasibility.

More precisely, the conflict graph is a directed acyclic graph in which the vertices¹ represent bound changes of variables, e.g., $x_i \leq \lambda_i$ or $x_i \geq \mu_i$. The conflict graph is built such that when the solver infers a bound change v as a consequence of a set of existing bound changes U , i.e., $U \rightarrow v$, then we have an arc (u, v) from each $u \in U$ to v . Bound changes caused by branching decisions are vertices without incoming edges. Finally the conflict graph includes a dummy vertex *false* representing failure which is added when the solver infers unsatisfiability.

Given a conflict graph, each cut that separates the branching decisions from the artificial infeasibility vertex *false* gives rise to a valid conflict constraint. A *unique implication point (UIP)* is an (inner) vertex of the conflict graph which is traversed by all paths from the branching vertices to the conflict vertex. Or, how Zhang et al. [43] describe it: “Intuitively, a UIP is the *single* reason that implies the conflict at [the] current decision level.” UIPs are natural candidates for finding small cuts in the conflict graph. The *1-UIP* is the first cut separating the conflict vertex from the branching decisions when traversing in reverse assignment order.

For integer programs, conflict constraints can be expressed as so-called *bound disjunction* constraints:

Definition 2 For an IP, let $\mathcal{L} \subseteq \mathcal{I}, \mathcal{U} \subseteq \mathcal{I}$ be disjoint index sets of variables, let $\lambda \in \mathbb{Z}^{\mathcal{L}}$ with $l_i \leq \lambda_i \leq u_i$ for all $i \in \mathcal{L}$, and $\mu \in \mathbb{Z}^{\mathcal{U}}$ with $l_i \leq \mu_i \leq u_i$ for all $i \in \mathcal{U}$. Then, a constraint of the form

$$\bigvee_{i \in \mathcal{L}} (x_i \geq \lambda_i) \vee \bigvee_{i \in \mathcal{U}} (x_i \leq \mu_i)$$

is called a *bound disjunction constraint*.

¹For disambiguation, we will use the term *vertex* for elements of the conflict graph, as opposed to *nodes* of the search tree.

For details on bound disjunction constraints, see Achterberg [1]. If all involved conflict values λ, μ correspond to global bounds of the variables, the bound disjunction constraint can be equivalently expressed as a knapsack constraint of form

$$\sum_{i \in \mathcal{U}} x_i - \sum_{i \in \mathcal{L}} x_i \leq \sum_{i \in \mathcal{U}} u_i - \sum_{i \in \mathcal{L}} l_i - 1. \quad (2)$$

Note that for BPs all conflicts only involve global bounds.

The power of conflict learning arises because often branch-and-bound based algorithms implicitly repeat the same search in a slightly different context in another part of the tree. Conflict constraints help to avoid redundant work in such situations. As a consequence, the more search is performed by a solver and the earlier conflicts are detected, the greater the chance for conflict learning to be beneficial. Note that conflict generation has a positive interaction with depth-first search. Depth-first search leads to the creation of no-goods that explain why a whole subtree contains no solutions, and hence the no-goods generated by depth-first search are likely to prune more of the subsequent search.

3 Rapid Learning for Integer Programs

The principle motivation for Rapid Learning [13] is the fact that a CP solver can typically search hundreds or thousand of nodes in a fraction of the time that a MIP solver needs for processing the root node of the search tree. Rapid Learning applies a fast CP search² for a few hundred or thousand nodes, before starting the MIP search. Using this approach, conflict constraints can be learnt before, and not only during, MIP search. Very loosely speaking: while the aim of conflict learning is to avoid making mistakes a second time, Rapid Learning tries to avoid making them the first time (during MIP search).

Rapid Learning is related to large neighborhood search heuristics, such as RINS and RENS [12, 20]. But, rather than doing an incomplete search on a subproblem using the same (MIP search) algorithm, Rapid Learning performs an incomplete search on the same problem using a much faster algorithm (CP search). Rapid Learning differs from primal heuristics in that it aims at improving the dual bound by collecting information on infeasibility rather than searching for feasible solutions.

Each piece of information collected in a rapid CP search can be used to guide the MIP search or even deduce further reductions during root node processing. Since the CP solver is solving the same problem as the MIP solver

- each generated conflict constraint is valid for the MIP search,
- each global bound change can be applied at the MIP root node,
- each feasible solution can be added to the MIP solver’s solution pool,

²By CP search we mean applying a depth-first search using only propagation for reasoning, no LP relaxation is solved during the search.

- the branching statistics can initialize a hybrid MIP branching rule, see [4], and
- if the CP solver completely solves the problem, the MIP solver can abort.

All five types of information may be beneficial for a MIP solver, and are potentially generated by our algorithm which we now describe more formally.

The Rapid Learning algorithm is outlined in Figure 1. Here, $l(P)$ and $u(P)$ are lower and upper bound vectors, respectively, of the problem at hand, P . For the moment we assume P is the root problem, in the next section we will examine the use of Rapid Learning at subproblem nodes. The symbol C refers to a single globally valid conflict constraint explaining the infeasibility of the current subproblem. Rapid Learning is an incomplete CP search: a branch-and-bound algorithm which traverses the search space in a depth-first manner (Line 3), using propagation (Line 4) and conflict analysis (Line 7), but no LP relaxation. Instead, the *pseudo-solution* [2], i.e., an optimal solution of a relaxation consisting only of the variable bounds (Line 5), is used for the bounding step.

Propagation of linear constraints is conducted by the bound strengthening technique of Brearley et al. [18] which uses the residual activity of linear constraints within the local bounds. For special cases of linear constraints, SCIP implements special, more efficient propagators. Knapsack constraints use efficient integer arithmetic instead of floating point arithmetic, and sort by coefficient values to propagate each variable only once. SCIP also features methods to extract clique information about the binary variables of a problem. A clique is a set of binary variables of which at most one variable can take the value 1 in a feasible solution. Clique information can be used to strengthen the propagation of knapsack constraints. Set cover constraints are propagated by the highly efficient two-watched literal scheme [33], which is based on the fact that the only domain reduction to be inferred from a set cover constraint is to fix a variable to 1 if all other variables have already been fixed to 0.

Variable and value selection takes place in Line 14; inference branching [2] is used as branching rule. Inference branching maintains statistics about how often the fixing of a variable led to fixings of other variables, i.e., it is a history rule, its essentially a MIP equivalent of impact-based search [29, 36]. Since history rules are often weak in the beginning of the search, we seed the CP solver with statistics that the MIP solver has collected in probing [39] during MIP presolving.

We assume that the propagation routines in Line 4 may also deduce global bound changes and modify the global bound vectors $l(P)$ and $u(P)$. Single-clause conflicts are automatically upgraded to global bound changes in Line 9. Note that it suffices to check constraint feasibility in Line 11, since the pseudo-solution \bar{x} (see Line 5) will always take the value of one of the (integral) bounds for each variable.

Our implementation of the Rapid Learning heuristic uses a secondary SCIP instance to perform the CP search. Only a few parameters need to be altered from their default values to turn SCIP into a CP solver, an overview is given in

Figure 1: Rapid Learning algorithm

Input : IP P as in (1) (with $\mathcal{R} = \emptyset$),
node limit lim_{node} ,
primal bound \bar{c} for P (might be ∞)

Output: set of valid conflict constraints \mathcal{L}_C for P ,
valid global domain box $[l, u]$ for P ,
feasible solution \tilde{x} for P or \emptyset

```

1  $\mathcal{L} \leftarrow \{P\}$ ,  $n_{\text{node}} \leftarrow 0$ ,  $\mathcal{L}_C \leftarrow \emptyset$ ,  $\tilde{x} \leftarrow \emptyset$ ;
2 while  $\mathcal{L} \neq \emptyset \wedge n_{\text{node}} < \text{lim}_{\text{node}}$  do
3    $\tilde{P} \leftarrow \text{select\_dfs}(\mathcal{L})$ ,  $\mathcal{L} \leftarrow \mathcal{L} \setminus \tilde{P}$ ,  $n_{\text{node}} \leftarrow n_{\text{node}} + 1$ ;
4    $[l(\tilde{P}), u(\tilde{P})] \leftarrow \text{propagate}([l(\tilde{P}), u(\tilde{P})])$ ;
5    $\tilde{x} \leftarrow \text{argmin}\{c^T x \mid x \in [l(\tilde{P}), u(\tilde{P})]\}$ ;

   /* analyze infeasible subproblem, potentially store
   globally valid conflict constraint */
6   if  $[l(\tilde{P}), u(\tilde{P})] = \emptyset$  or  $c(\tilde{x}) \geq \bar{c}$  then
7      $C \leftarrow \text{analyze}(\tilde{P})$ ;
8     if  $C \neq \emptyset$  then  $\mathcal{L}_C \leftarrow \mathcal{L}_C \cup \{C\}$ ;
9     if  $|C| = 1$  then  $\text{tighten}([l(P), u(P)])$ ;
10    continue;

   /* check for new incumbent solution */
11   if  $A\tilde{x} \leq b$  and  $c^T \tilde{x} < \bar{c}$  then
12      $\tilde{x} \leftarrow \tilde{x}$ ,  $\bar{c} \leftarrow c^T \tilde{x}$ ;
13     continue;

14    $(x_i, v) \leftarrow \text{select\_infer}(\tilde{P}, \tilde{x})$ ;
15    $\tilde{P}_l \leftarrow \tilde{P} \cup \{x_i \leq v\}$ ,  $\tilde{P}_r \leftarrow \tilde{P} \cup \{x_i \geq v\}$ ;
16    $\mathcal{L} \leftarrow \mathcal{L} \cup \{\tilde{P}_l, \tilde{P}_r\}$ ;
17 return  $(\mathcal{L}_C, [l(P), u(P)], \tilde{x})$ ;

```

Table 1. Most importantly, we disabled the LP relaxation and use a pure depth-first search with inference branching (but without any additional tie breakers). Further, we switch from All-UIP to 1-UIP in order to generate only one conflict per infeasibility. This is a typical behavior of CP solvers, but not for MIP solvers. Expensive feasibility checks and propagation of the objective function as a constraint are also avoided.

In order to avoid spending too much time in Rapid Learning, the number of nodes explored during the CP search is limited to at most 5000. The actual number of allowed nodes is determined by the number of simplex iterations

Table 1: Settings for Rapid Learning sub-SCIP.

parameter name	value	effect
lp/solvefreq	-1	disable LP
conflict/fuilevels	1	use 1-UIP
nodeselection/dfs/stdpriority	$\text{INT_MAX}/4$	use DFS
branching/inference/useweightedsum	FALSE	pure inference, no VSIDS
constraints/disablefops	TRUE	no extra checks
propagating/pseudoobj/freq	-1	no objective propagation
conflict/maxvarsfac	0.05	only short conflicts
history/valuebased	TRUE	extensive branch. statistics

iter_{LP} performed so far in the main SCIP but at least 500, i.e.,

$$\text{lim}_{\text{node}} = \min\{5000, \max\{500, \text{iter}_{\text{LP}}\}\}.$$

The idea is to restrict Rapid Learning more rigorously for problems where processing of a single MIP node is cheap already. The number of simplex iterations is a deterministic estimate for node processing cost.

We aim to generate short conflict constraints, since these are most likely to frequently trigger propagations in the upcoming MIP search. Thus, we only collect conflicts that contain at most 5% of the problem variables. Finally, we adapt the collection of branching statistics such that history information on general integer variables are collected per value in the domain rather than having one counter for down- and one for up-branches regardless of the value on which was branched. This can be essential for performing an efficient CP search on general integer variables, and was a building block that enabled us to use Rapid Learning on IPs rather than solely on BPs, as in [13].

In addition to the particular parameters listed in Table 1, we set the emphasis³ for presolving to “fast”. Emphasis settings for cutting are not necessary, since no LP relaxation is solved, from the armada of primal heuristics only a few are applied that do not require an LP relaxation, see [5]. Note that since Rapid Learning will be called at the end of the MIP root node, or even locally, see next Section, the problem that the CP solver considers has already been presolved, might contain cutting planes as additional linear constraints and have an objective cutoff constraint if a primal solution has been found by a primal heuristic during root node processing.

4 Local Rapid Learning

The original Rapid Learning algorithm [13] was used as part of a root preprocessing, i.e., for every instance it was run exactly once at the end of the root node. But only running Rapid Learning at the root limits its effectiveness. We

³In SCIP, emphasis settings correspond to a group of individual parameters being changed.

now discuss the factors that arise when we allow Rapid Learning to be run at local nodes inside the search tree

When running in the root only all information returned by the CP solver is globally valid, and the overhead to maintain the information gathered by Rapid Learning is negligible [13]. In contrast, when applying Rapid Learning at a local node within the tree conflicts and bound changes will only be locally valid in general. Since Rapid Learning uses a secondary SCIP instance to perform the CP search, all local information of the current node becomes part of the initial problem formulation for the CP search. Thus, conflicts gathered by Rapid Learning do not include bound changes made along the path from the root to the current node, they are simply considered as valid for this local node. As a consequence, these conflicts will only be locally valid and hence only applied to the current node of the MIP search. Using an assumption interface [34], local conflicts could be lifted to be globally valid. However, this is subject to future investigation and not considered in the current implementation of Rapid Learning.

In practice, all local information needs to be maintained when switching from one node of the tree to another. In CP solvers, switching nodes is typically very cheap, because depth-first search is used. However, a MIP solver frequently “jumps” within the tree. Therefore, two consecutively processed nodes can be quite different. In what follows, we will refer to the time spent for moving from one node to another node as *switching time*. The switching time can be used as an indicator to quantify the overhead introduced by all locally added information found by Rapid Learning.

To ensure that the amount of locally added information does not increase the switching time too much, we apply Rapid Learning very rarely by using an exponentially decreasing frequency of execution. Rapid Learning is executed at every node of depth d with

$$\log_{\beta}(d/f) \in \mathbb{Z}, \quad (3)$$

where β and f are two parameters to control the speed of decrease. For example, if $\beta = 1$ Rapid Learning is executed at every depth $d = i \cdot f$ with $i \in \mathbb{Z}_+$.

Unfortunately, the amount of locally valid information produced by Rapid Learning still leads to an increase of switching time by 21%. Consequently, the overall performance decreased by 20% in our first experiments. At the same time the number of explored branch-and-bound nodes decreased by 16%. This indicates the potential gains possible using local Rapid Learning.

To control at which subproblem Rapid Learning is applied we propose six criteria to forecast the potential of Rapid Learning. These criteria aim at identifying one of two situations. The first is to estimate whether the (sub)problem is infeasible or a pure feasibility problem. In these cases propagating conflicts is expected to be particularly beneficial. The second is to estimate the dual degeneracy of a problem. In this case, VSIDS branching statistics are expected to be particularly beneficial. The VSIDS [31] (variable state independent decaying sum) statistics takes the contribution of every variable (and its negated complement) in conflict constraints found so far into account. For every variable, the

number of clauses (in MIP speaking: conflict constraints) the variable is part of is counted. In the remainder of the search the VSIDS are periodically scaled by a predefined constant. By this, the weight of older clauses is reduced over time and more recent observations have a bigger impact.

A basic solution of an LP is called *dual degenerate*, when it has nonbasic variables with zero reduced costs. One can define the dual degeneracy of a MIP as the average number of nonbasic variables with zero reduced costs appearing in a basic solution of its LP relaxation. The higher the dual degeneracy, the higher the chance that the LP objective will not change by branching and hence many of the costs involved in the pseudo-cost computation are zero. Therefore, for highly dual degenerate problems, using other branching criteria, such as VSIDS or inference scores, is crucial for solving the problem.

We now describe the six criteria we use to identify infeasible or dual degenerate problems, already using the criteria abbreviations from the tables in Section 5:

Criterion I: Dual Bound Improvement. During the tree search a valid lower bound for each individual subproblem is given by the respective LP solution. A globally valid lower bound is given by the minimum over all individual lower bounds. This global bound is called the *dual bound*. If the dual bound has not changed after processing a certain number of nodes, i.e., the dual bound is equal to the lower bound of the root node, it might be the case that the MIP lies inside a level plane of the objective, i.e., all feasible LP (and MIP) solutions will have the same objective. In other words, the instance might be a feasibility instance for which Rapid Learning was already shown to be very successful [13]. Feasibility instances are typically highly dual degenerate. The `dualbound` criterion means to call local Rapid Learning if the dual bound never changed during the MIP search.

Criterion II: Leaves Pruned by Infeasibility or Exceeding the Cutoff bound. During the tree search every leaf node either provides a new incumbent solution (the rare case), is proven to be infeasible or to exceed the current cutoff bound which is given by the incumbent solution. The ratio of the latter two cases is used in SCIP’s default branching rule. *Hybrid branching* [4] combines pseudo-costs, inference scores, and conflict information into one single branching score. The current implementation in SCIP puts a higher weight on conflict information, e.g., VSIDS [31], and a lower weight on pseudo-costs when the ratio of infeasible and cutoff nodes is larger than a predefined threshold. The `leaves` criterion means to call local Rapid Learning if the ratio of infeasible leaves over those exceeding the cutoff bound is larger than 10. The rationale is that we expect (local) conflicts to be most beneficial, when infeasibility detection appears to be the main driver for pruning the tree.

Criterion III: LP Degeneracy. As mentioned above, the more nonbasic variables are dual degenerate, the less information can be gained during strong

branching or pseudo-cost computation. As a consequence, Berthold et al. [14] introduced a modification to strong branching that considers the dual degeneracy of the LP solution. In rough terms, if either the share of dual degenerate nonbasic variables or the variable-constraint ratio of the optimal face exceed certain thresholds, strong branching will be deactivated. We adapt this idea of using the dual degeneracy of the current LP solution. The `degeneracy` criterion means to call local Rapid Learning if more than 80% of the nonbasic variables are degenerate or the variable-constraint ratio of the optimal face is larger than 2, as proposed in [14]. In both cases we expect that “strong conflict generation” will be useful.

Criterion IV: (Local) Objective Function. If all variables with non-zero objective coefficients are fixed at the local subproblem, i.e., the objective is constant, Criteria I and II will apply: every LP solution is fully dual degenerate and the only possibility to prune a leaf node is by infeasibility. If there are only very few unfixed variables with nonzero objective are left, the criteria might not apply. However, it is likely that the targeted situations occur frequently in the tree rooted at the current subproblem, at the latest, when all the variables occurring in the objective are fixed. The `obj` criterion means to call local Rapid Learning once the objective support is small enough, in anticipation of the current subproblem turning into a feasibility problem. In our implementation we apply this criterion very conservatively, and call Rapid Learning only if the local objective is zero.

Criterion V: Number of Solutions. The most obvious evidence, and indeed a necessary one, that a MIP instance is infeasible, is that no feasible solution has been found during the course of the MIP search. Note that for most (feasible) MIP instances, primal heuristics find a feasible solution at the root node [11] or at the latest during the first dive in the branch-and-bound. The `nsols` criterion means to call local Rapid Learning if no feasible solution has been found so far.

Criterion VI: Strong Branching Improvements. In the beginning of the tree search it is very unlikely that enough leaf nodes are explored to reliably guess whether the actual MIP is a feasibility instance. Therefore, we consider the subproblems evaluated during strong branching, which are concentrated at the top of the search tree. Similarly to Criterion II, we compute the ratio between the number of strong branching problems that gave no improvement in the objective or went infeasible to the number of strong branching problems where we observed an objective change. The `sblps` criterion means to call local Rapid Learning if this ratio exceeds a threshold of 10, hence strong branching does not appear to be efficient for generating pseudo-cost information.

In addition to the exponentially decreasing frequency and the six criteria above, we applied the following three changes to the original implementation of Rapid Learning used in [13].

- We limited the number of conflict constraints transferred from Rapid Learning back to the original search tree to ten. This corresponds to the SCIP parameter `conflict/maxconss` for the maximal allowed number of added conflicts per call of conflict analysis. We greedily use the shortest conflicts.
- We prefer conflict constraints that have a linear representation over bound disjunction constraints (see Definition 2).
- To exploit performance variability [19, 30] every CP search is initialized with a different pseudo-random seed.

5 Computational results

To evaluate how local Rapid Learning impacts IP solving performance we used the academic constraint integer programming solver SCIP 6.0 [24] (with SOPLEX 4.0 as LP solver) and extended the existing code of Rapid Learning. The original implementation of Rapid Learning was already shown to significantly improve the performance of SCIP 1.2.0.5 on pure binary instances [13]. In this setting, Rapid Learning was applied exactly once at the root node. However, during the last eight years SCIP has changed in many places. In SCIP 6.0, Rapid Learning is deactivated by default, since it led to a big performance variability.

Therefore, we use SCIP without Rapid Learning (as it is the current default) as a baseline. We will refer to this setting as `default`. In our computational experiments we evaluate the impact of local Rapid Learning if one or more of the criteria described in Section 4 are fulfilled. In the following, we will refer to the criteria I–VI as `dualbound`, `leaves`, `degeneracy`, `obj`, `nsols`, and `sbtps`, respectively. Within the tree, Rapid Learning is applied with an exponentially decreasing frequency (see Section 4). In our experiments, we used $f = 5$ and $\beta = 4$, i.e., Rapid Learning is called at depths d with $\log_4(d/5) \in \mathbb{Z}$, i.e., $d = 0, 5, 20, 80, 320 \dots$, if one of the six criteria is fulfilled.

As a test set we used all pure integer problems of MIPLIB 3 [16], MIPLIB 2003 [8] and the MIPLIB 2010 [28] benchmark set. This test set consists of 71 publicly available instances, which we will refer to as MMM-IP. To account for the effect of performance variability [19, 30] all experiments were performed with five different global random seeds. Every pair of instance and seed was treated as an individual observation, effectively resulting in a test set of 355 instances. We will use the term “instance” when actually referring to an instance-seed-combination. The experiments were run on a cluster of identical machines, each with an Intel Xeon E5-2690 with 2.6 GHz and 128 GB of RAM; a time limit of 3600 seconds was set.

In a first experiment we evaluated the efficacy of each individual criterion and global Rapid Learning as published in [13]. Aggregated results are shown in Table 2, section Exp.1. For detailed results see Table 4 in the appendix. For every setting, the table shows the number of solved instances out of 71

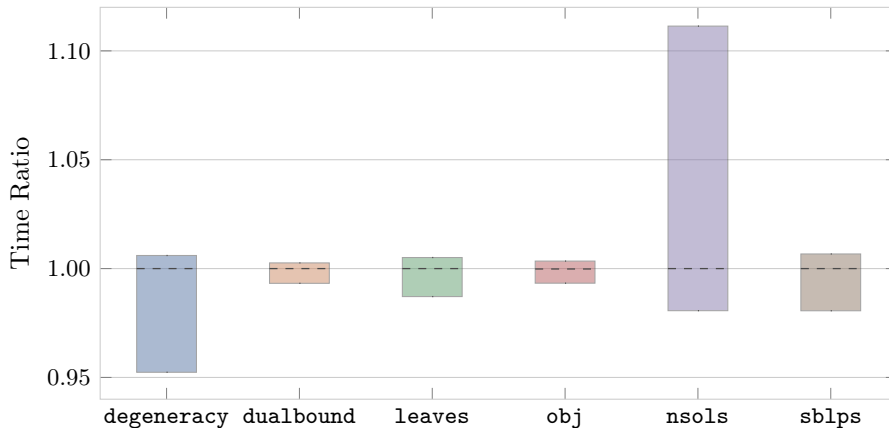


Figure 2: Box-plot of the performance ratios of the individual criteria compared to `default` on the set of affected instances.

(`solved`), shifted geometric means [3] of the absolute solving time in seconds (`time`, `shift = 1`) and number of explored nodes (`nodes`, `shift = 100`), as well as the relative solving time (`timeQ`) and number of nodes (`nodesQ`) w.r.t. to `default` as a baseline. Local Rapid Learning without any of the presented criteria (`nochecks`) leads to a performance decrease of 20% on the complete test set MMM-IP compared to `default`. Always applying Rapid Learning only at the root (`onlyroot`), which corresponds to Rapid Learning as published in [13], leads to slowdown of 7.8% but solves three instance more. For this settings, we could observe a performance decrease of 38.1% on the group of instances that are not affected⁴ by Rapid Learning. To avoid a computational overhead and performance variability on instances where Rapid Learning is not expected to be beneficial, we apply the criteria `degeneracy`, `obj`, and `nsols` at the root node, too. Afterwards, the performance decrease of global Rapid Learning reduced to 0.9%. The computational results indicate that almost all individual criteria are useful on their own. The solving time and generated nodes can be reduced by up to 6% and 15%, respectively, on the complete test set of 71. The exception is the `obj` criterion, which leads to a marginal slowdown of 0.6%, but solves three more instance than `default`. On the group of affected instances the solving time and number of generated nodes can be reduced up to 8% and 19%, respectively, both by using `degeneracy`.

The impact of the individual criteria on the solving time is illustrated in Figure 2. For each criterion, the box plot [32] shows the median (dashed line), and the 1st and 3rd quartile (shaded box) of all observations. The plot shows that `degeneracy` performs best since it leads by far to the best improvement on the 1st quartile. In contrast to that, the 3rd quartile of `nsols` indicates this criterion leads to a deterioration of more than 10% on 25% of the instances.

⁴An instance is called affected when the solving path changes.

Table 2: Computational results for every individual heuristic criterion on MMM-IP.

		solved	time	nodes	time _Q	nodes _Q
Exp.1	default	304	50.92	2466	–	–
	degeneracy	306	48.02	2084	0.943	0.845
	dualbound	304	50.26	2369	0.987	0.961
	leaves	305	49.31	2347	0.968	0.952
	obj	307	51.23	2399	1.006	0.973
	nsols	304	47.94	2142	0.941	0.869
	sblps	304	50.38	2296	0.989	0.931
	nochecks	299	61.10	1925	1.200	0.781
	onlyroot	307	54.89	2404	1.078	0.975
Exp.2	degeneracy + leaves	306	47.81	2073	0.939	0.841
	leaves + obj	307	49.80	2284	0.978	0.926
	all6criterion	303	48.23	2030	0.947	0.823

Grouping all instances of MMM-IP based on the degeneracy at the end of the root node shows the importance of this criterion. On the group of instances where at least 1% of the variables is dual degenerate at the end of the root node Rapid Learning leads to a performance improvement of 9.1%. On all instances where at least 80% of the variable are dual degenerate at the root node, we could observe a reduction of solving time by 28.8%. Note that this was one of the two thresholds for the **degeneracy** criterion.

In a second experiment (Table 2, section Exp.2; Table 5 in the appendix) we combined all individual criteria. Combining two or more criteria leads to more aggressive version of Rapid Learning since it runs if at least one of the chosen criteria is satisfied. The two (out of fifteen) best pairwise combinations as well as the (most aggressive) combination of all six criteria are shown in Table 2. Interestingly, no combined setting is superior to **degeneracy**. The combination of **degeneracy** and **leaves**, which were the two outstanding criteria in the individual test, performs almost the same as the **degeneracy** criterion alone.

For a final experiment we choose **degeneracy** as the best criterion, since it was one of two criteria that solved an additional instance, clearly showed the best search reduction, and was a close second to **leaves** with respect to running time. Our final experiment evaluates the impact of the individual information gained from local Rapid Learning. To this end, we individually deactivated transferring variable bounds, conflict constraints, inference information, and primal feasible solutions (see Table 3; Table 6 in the appendix). This experiment indicates that primal solutions are the most important information for the remainder of the MIP search. When ignoring solutions found during the CP search, the overall solving time increased by 9.9% (**primsols**). When ignoring conflict constraints, the original motivation of Rapid Learning, solving time increased by 4.4% (**conflicts**). Both transferring variable bounds and inference information proved beneficial, with a 1.4% (**variablebounds**) and 0.6%

Table 3: Performance impact of individual gained information on MMM-IP.

		solved	time	nodes	time_Q	nodes_Q
Exp.3	degeneracy	306	48.02	2084	–	–
	variablebounds	305	48.69	2089	1.014	1.002
	conflicts	306	50.11	2225	1.044	1.067
	infervals	305	48.29	2179	1.006	1.046
	primsols	305	52.77	2349	1.099	1.127

(**infervals**) impact on performance, respectively. It is not surprising that finding primal solutions has the largest effect. Firstly, they are applied globally, in contrast to bound changes and conflicts. Secondly, highly dual degenerate problems are known to be cumbersome not only for MIP branching but also for primal heuristics [11], which means that solution-generating procedures that do not rely on solving LPs are particularly promising for such problems.

6 Conclusion

In this paper, we extended the idea of Rapid Learning [13]. Firstly, we generalized Rapid Learning to integer programs and described the details that were necessary for doing so: value-based inference branching, additional propagators and generalized conflict constraints, most of which were already available in SCIP. Secondly, we applied Rapid Learning repeatedly during the search. This generates a true hybrid CP/MIP approach, with two markedly different search strategies communicating information forth and back. To this end, we introduced six heuristic criteria to decide when to start local Rapid Learning. Those criteria are based on degeneracy information, branch-and-bound statistics, and the local structure of the problem. Our computational experiments showed a speed-up of up to 7% when applying local Rapid Learning in SCIP. Calling local Rapid Learning depending on the local degree of dual degeneracy is the best strategy found in our experiments.

Interesting future work in this direction includes: extending the CP search to generate global conflicts at local nodes using an assumption interface, running the CP search in a parallel thread where whenever the MIP solver moves to a new node the CP search restarts from that node, and extending the method to handle problems that include continuous variables.

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sbtps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
10teams	2.14	1	<i>1.277</i>	1.000	0.990	1.000	0.994	1.000	0.990	1.000	<i>1.271</i>	1.000	0.994	1.000	<i>1.248</i>	1.000	<i>1.258</i>	1.000
	20.00	1369	0.241	0.072	<i>1.290</i>	0.687	<i>1.236</i>	1.001	0.995	1.000	0.244	0.072	0.963	0.303	0.245	0.072	0.246	0.072
	15.57	287	<i>1.607</i>	<i>2.729</i>	<i>2.062</i>	<i>4.067</i>	0.998	1.000	1.006	1.000	<i>1.308</i>	<i>2.729</i>	<i>2.080</i>	<i>4.238</i>	<i>1.341</i>	0.829	0.672	0.323
	4.16	5	<i>2.721</i>	<i>1.219</i>	1.000	1.000	1.006	1.000	0.996	1.000	<i>2.713</i>	<i>1.219</i>	1.004	1.000	<i>2.709</i>	<i>1.219</i>	<i>2.329</i>	<i>1.219</i>
4.94	5	0.909	1.000	1.000	1.000	1.002	1.000	1.007	1.000	0.909	1.000	0.995	1.000	0.912	1.000	0.914	1.000	
30n20b8	314.13	195	0.605	0.553	1.002	1.000	1.001	1.000	0.990	1.000	0.289	0.346	0.999	1.000	0.285	0.346	0.289	0.346
	157.33	71	0.712	0.596	0.999	1.000	0.998	1.000	0.995	1.000	0.810	0.596	0.999	1.000	0.789	0.596	0.852	0.596
	87.25	4	1.001	1.000	1.000	1.000	1.003	1.000	0.998	1.000	<i>1.191</i>	1.000	0.997	1.000	<i>1.180</i>	0.981	<i>1.188</i>	1.000
	213.06	102	<i>1.208</i>	<i>1.312</i>	0.996	1.000	0.991	1.000	0.978	0.950	<i>1.251</i>	0.896	0.993	1.000	1.047	0.782	<i>1.251</i>	0.896
	470.09	290	0.811	0.723	0.998	1.000	1.003	1.000	0.998	1.000	0.238	0.423	0.996	1.000	0.241	0.421	0.238	0.423
acc-tight5	125.35	172	<i>1.114</i>	<i>1.171</i>	0.387	0.295	0.423	0.302	1.011	0.965	0.651	0.735	0.991	1.000	<i>1.087</i>	<i>1.171</i>	<i>1.115</i>	<i>1.622</i>
	84.38	98	<i>1.310</i>	<i>2.072</i>	<i>1.512</i>	<i>1.286</i>	0.448	0.326	0.856	0.551	<i>1.786</i>	<i>2.650</i>	0.991	1.000	<i>1.792</i>	<i>2.650</i>	0.721	0.952
	50.45	480	0.973	0.929	<i>2.656</i>	<i>2.631</i>	<i>1.753</i>	<i>1.966</i>	1.022	0.993	0.973	0.929	1.002	1.000	0.974	0.929	<i>3.299</i>	<i>6.017</i>
	85.88	87	0.340	0.189	<i>1.590</i>	<i>1.794</i>	0.401	0.290	0.420	0.274	0.339	0.189	1.000	1.000	0.340	0.189	<i>1.464</i>	<i>1.891</i>
	73.38	864	0.417	0.161	<i>1.440</i>	<i>1.091</i>	<i>2.064</i>	<i>1.326</i>	<i>1.488</i>	<i>1.309</i>	0.417	0.161	0.996	1.000	0.419	0.161	<i>1.256</i>	<i>1.088</i>
air03	1.70	1	1.011	1.000	1.015	1.000	1.015	1.000	1.015	1.000	1.004	1.000	1.007	1.000	<i>6.433</i>	1.000	<i>6.515</i>	1.000
	1.71	1	1.004	1.000	1.004	1.000	1.011	1.000	1.004	1.000	0.996	1.000	1.007	1.000	<i>6.590</i>	1.000	<i>6.472</i>	1.000
	1.74	1	0.993	1.000	1.011	1.000	1.004	1.000	0.989	1.000	1.000	1.000	0.985	1.000	<i>6.365</i>	1.000	<i>6.372</i>	1.000
	1.75	1	1.000	1.000	0.996	1.000	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000	<i>6.378</i>	1.000	<i>6.335</i>	1.000
	1.75	1	0.996	1.000	0.993	1.000	0.985	1.000	0.985	1.000	0.993	1.000	1.004	1.000	<i>6.491</i>	1.000	<i>6.378</i>	1.000
air04	49.46	110	1.003	1.000	1.007	1.000	1.008	1.000	1.005	1.000	1.003	1.000	1.006	1.000	0.978	0.776	0.911	0.652
	36.09	39	1.008	1.000	1.003	1.000	1.004	1.000	0.996	1.000	1.000	1.000	1.002	1.000	<i>1.172</i>	<i>1.144</i>	<i>1.112</i>	<i>1.158</i>
	52.88	118	1.005	1.000	1.000	1.000	1.002	1.000	0.999	1.000	0.997	1.000	0.990	1.000	0.993	0.665	0.949	0.665
	36.56	31	1.014	1.000	1.007	1.000	1.010	1.000	1.001	1.000	0.995	1.000	1.010	1.000	<i>1.552</i>	<i>1.481</i>	<i>1.735</i>	<i>3.061</i>
	48.35	122	1.006	1.000	1.002	1.000	1.004	1.000	1.001	1.000	1.004	1.000	1.003	1.000	0.803	0.500	0.801	0.500
air05	24.82	189	0.990	1.000	0.996	1.000	0.999	1.000	1.006	1.000	1.003	1.000	0.990	1.000	<i>2.135</i>	<i>1.388</i>	<i>1.270</i>	<i>1.547</i>
	26.54	239	1.004	1.000	1.005	1.000	1.001	1.000	1.008	1.000	1.001	1.000	1.003	1.000	<i>3.006</i>	<i>1.714</i>	<i>1.275</i>	<i>1.419</i>
	31.37	438	0.992	1.000	0.992	1.000	0.997	1.000	0.996	1.000	0.994	1.000	0.997	1.000	<i>1.869</i>	0.690	<i>1.132</i>	0.946
	27.36	283	1.007	1.000	1.006	1.000	1.006	1.000	1.007	1.000	1.006	1.000	0.996	1.000	<i>1.679</i>	<i>1.222</i>	<i>1.175</i>	<i>1.204</i>
	27.14	279	1.003	1.000	1.003	1.000	1.002	1.000	1.002	1.000	1.004	1.000	0.996	1.000	<i>2.084</i>	<i>1.343</i>	<i>1.128</i>	0.934
blend2	0.69	714	1.041	1.000	1.041	1.000	1.036	1.000	1.047	1.000	1.041	1.000	1.047	1.000	1.041	1.000	1.041	1.000
	1.08	973	0.986	1.000	1.005	1.000	0.971	1.000	1.019	1.000	1.005	1.000	0.971	1.000	1.010	1.000	0.986	1.000
	1.05	912	1.005	1.000	0.995	1.000	0.990	1.000	1.000	1.000	0.985	1.000	1.000	1.000	1.000	1.000	0.995	1.000
	0.67	543	0.994	1.000	1.006	1.000	1.012	1.000	1.030	1.000	1.000	1.000	1.012	1.000	1.012	1.000	1.018	1.000
	0.66	709	1.030	1.000	1.018	1.000	1.018	1.000	1.006	1.000	1.036	1.000	1.042	1.000	1.024	1.000	1.030	1.000
bley_x11	164.49	1	0.997	1.000	1.002	1.000	0.998	1.000	1.000	1.000	1.008	1.000	0.996	1.000	0.997	1.000	1.003	1.000
	187.04	3	1.012	<i>1.146</i>	1.007	1.000	1.005	1.000	1.002	1.000	1.005	1.000	1.003	1.000	0.906	0.981	0.907	0.981
	182.51	13	0.892	0.903	1.012	1.000	1.015	1.000	1.012	1.000	1.013	1.000	1.001	0.956	0.901	0.903	0.898	0.903
	133.90	1	1.006	1.000	1.008	1.000	1.003	1.000	1.005	1.000	1.005	1.000	1.011	1.000	0.982	1.000	<i>1.118</i>	1.000

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sbtps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	135.56	1	1.006	1.000	1.006	1.000	1.001	1.000	1.000	1.000	1.005	1.000	1.008	1.000	1.014	1.000	1.023	1.000
bnatt350	378.09	89	0.052	0.030	0.431	0.301	0.107	0.054	<i>3.061</i>	<i>2.782</i>	0.053	0.030	0.121	0.041	0.052	0.030	<i>2.109</i>	<i>2.434</i>
	521.76	326	0.033	0.022	0.276	0.183	0.144	0.084	<i>1.081</i>	<i>1.382</i>	0.033	0.022	1.011	<i>1.431</i>	0.033	0.022	0.487	0.420
	397.10	160	0.048	0.026	0.119	0.057	0.131	0.063	0.610	0.445	0.048	0.026	0.301	0.229	0.048	0.026	0.889	0.846
	155.46	4028	0.109	0.067	0.262	0.129	<i>2.325</i>	<i>2.588</i>	<i>1.524</i>	<i>1.482</i>	0.109	0.067	0.389	0.127	0.110	0.067	<i>4.491</i>	<i>3.610</i>
	994.16	2528	0.044	0.021	0.575	0.724	0.329	0.259	0.713	0.670	0.044	0.021	0.156	0.076	0.045	0.021	0.317	0.315
cap6000	2.69	1830	1.003	1.000	1.019	1.000	1.003	1.000	1.019	1.000	1.016	1.000	0.989	1.000	<i>1.412</i>	<i>1.131</i>	<i>1.098</i>	0.866
	2.67	1837	0.986	1.000	0.984	1.000	0.989	1.000	0.986	1.000	0.975	1.000	1.003	1.000	<i>1.455</i>	<i>1.256</i>	<i>1.155</i>	<i>1.142</i>
	2.61	1959	0.992	1.000	1.000	1.000	0.997	1.000	1.006	1.000	0.997	1.000	0.992	1.000	<i>1.280</i>	0.982	<i>1.150</i>	<i>1.066</i>
	3.17	1924	1.007	1.000	0.990	1.000	1.007	1.000	0.993	1.000	0.995	1.000	0.995	1.000	<i>1.422</i>	<i>1.166</i>	<i>1.086</i>	0.894
	2.82	1762	1.008	1.000	1.008	1.000	0.995	1.000	0.987	1.000	0.995	1.000	1.008	1.000	<i>1.387</i>	<i>1.325</i>	<i>1.157</i>	<i>1.258</i>
cov1075	3600.00	1445091	0.989	<i>1.189</i>	1.000	0.981	1.000	0.996	1.000	1.004	1.000	0.991	1.000	0.985	1.000	0.314	0.961	<i>1.189</i>
	3600.00	1787171	1.000	0.975	1.000	0.982	1.000	0.998	1.000	1.004	1.000	1.003	1.000	0.989	1.000	0.303	1.000	0.989
	3600.00	1528146	1.000	<i>1.198</i>	1.000	0.986	1.000	0.998	1.000	0.997	1.000	0.999	1.000	0.956	1.000	0.373	1.000	<i>1.210</i>
	3600.00	1808088	1.000	0.985	1.000	0.995	1.000	1.006	1.000	1.002	1.000	1.006	1.000	0.974	1.000	0.250	0.997	0.995
	3600.00	1201194	1.000	<i>1.508</i>	1.000	0.986	1.000	0.997	1.000	0.999	1.000	1.000	1.000	0.898	1.000	0.460	0.979	<i>1.514</i>
csched010	3600.00	228369	1.000	1.003	1.000	1.001	1.000	0.963	1.000	0.999	0.758	0.644	1.000	1.001	1.000	0.571	0.907	0.925
	3600.00	175223	1.000	1.001	1.000	1.001	1.000	0.884	1.000	1.000	0.972	1.038	1.000	0.999	1.000	0.756	0.850	1.037
	2891.69	214060	1.000	1.000	0.951	0.941	<i>1.147</i>	<i>1.206</i>	0.997	1.000	<i>1.245</i>	<i>1.145</i>	1.002	1.000	<i>1.245</i>	0.689	<i>1.245</i>	<i>1.280</i>
	3600.00	195746	1.000	0.998	1.000	0.996	0.988	0.820	1.000	0.998	1.000	0.960	1.000	0.997	1.000	0.578	1.000	1.028
	3168.37	226703	1.001	1.000	0.999	1.000	<i>1.136</i>	<i>1.303</i>	1.000	1.000	<i>1.136</i>	<i>1.352</i>	1.001	1.000	<i>1.136</i>	0.682	<i>1.136</i>	<i>1.307</i>
eil33-2	69.44	583	1.003	1.000	1.034	1.000	1.005	1.000	1.034	1.000	1.031	1.000	1.008	1.000	<i>1.772</i>	0.909	<i>1.094</i>	0.909
	81.92	739	1.007	1.000	1.007	1.000	1.010	1.000	0.997	1.000	1.009	1.000	1.007	1.000	<i>1.671</i>	0.852	1.028	0.852
	84.87	847	0.989	1.000	0.999	1.000	1.001	1.000	1.001	1.000	1.008	1.000	1.002	1.000	<i>1.904</i>	0.852	<i>1.195</i>	0.852
	73.60	543	0.988	1.000	1.007	1.000	1.000	1.000	1.001	1.000	1.010	1.000	1.003	1.000	<i>2.006</i>	<i>1.509</i>	<i>1.260</i>	<i>2.728</i>
	70.01	583	0.987	1.000	1.007	1.000	1.002	1.000	1.002	1.000	1.007	1.000	1.003	1.000	<i>2.176</i>	<i>1.433</i>	<i>1.602</i>	<i>1.416</i>
eilB101	378.99	10582	0.998	1.000	1.021	1.000	1.002	1.000	1.023	1.000	0.999	1.000	1.009	1.000	<i>1.083</i>	0.724	0.705	0.724
	365.27	8427	0.984	1.000	0.995	1.000	0.993	1.000	0.999	1.000	1.005	1.000	0.997	1.000	<i>1.391</i>	<i>1.150</i>	0.916	<i>1.050</i>
	401.63	9358	0.995	1.000	1.000	1.000	0.998	1.000	0.993	1.000	1.008	1.000	0.997	1.000	<i>1.147</i>	0.780	0.819	0.780
	397.46	11465	0.996	1.000	0.999	1.000	0.998	1.000	0.999	1.000	1.002	1.000	0.995	1.000	<i>1.304</i>	1.025	0.905	1.025
	365.79	10006	0.989	1.000	0.998	1.000	0.989	1.000	0.994	1.000	0.996	1.000	1.001	1.000	<i>1.201</i>	0.894	0.818	0.894
enigma	0.50	809	1.000	0.825	1.020	0.716	1.000	1.000	1.000	0.998	1.000	0.542	<i>1.140</i>	0.686	1.000	0.542	1.000	0.856
	0.50	449	1.000	0.497	1.000	0.814	1.000	1.000	1.000	1.000	1.000	0.470	1.000	0.778	1.000	0.470	1.000	<i>1.616</i>
	0.50	541	1.000	0.254	1.000	0.510	1.000	1.000	1.000	0.977	1.000	0.237	<i>1.060</i>	0.721	1.000	0.237	1.000	0.665
	0.50	679	<i>1.073</i>	0.537	1.000	0.397	1.000	1.000	1.000	1.000	1.000	0.151	<i>1.133</i>	<i>1.113</i>	1.000	0.151	1.000	0.244
	0.50	445	1.020	0.543	1.000	0.833	1.000	1.000	1.000	1.006	1.000	0.543	1.000	0.806	1.013	0.543	1.000	<i>1.675</i>
enlight13	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Instance	default		degeneracy		dualbound		leaves		obj		nsols		sblps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
enlight14	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
fiber	1.00	2	1.010	1.000	1.010	1.000	0.990	1.000	1.005	1.000	1.000	1.000	1.000	1.000	<i>1.160</i>	1.010	<i>1.075</i>	1.010
	1.42	4	0.988	1.000	1.004	1.000	0.988	1.000	1.000	1.000	0.992	1.000	1.008	1.000	<i>1.384</i>	<i>1.240</i>	0.938	0.990
	1.74	4	1.007	1.000	0.993	1.000	0.996	1.000	0.996	1.000	0.978	1.000	0.982	1.000	<i>1.401</i>	1.010	0.949	0.990
	1.53	4	1.008	1.000	1.000	1.000	0.996	1.000	0.996	1.000	0.988	1.000	1.000	1.000	<i>1.194</i>	0.990	1.024	1.000
	1.00	3	1.000	1.000	1.005	1.000	1.005	1.000	1.000	1.000	0.995	1.000	1.005	1.000	<i>1.080</i>	0.990	1.030	0.990
flugpl	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
gt2	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
harp2	691.56	1491878	1.005	1.000	1.001	1.000	1.001	1.000	1.007	1.000	1.000	1.000	1.003	1.000	<i>5.200</i>	<i>5.260</i>	<i>4.215</i>	<i>4.834</i>
	1159.66	2857677	1.004	1.000	0.998	1.000	0.994	1.000	0.998	1.000	0.993	1.000	0.994	1.000	0.410	0.228	<i>2.318</i>	<i>2.253</i>
	336.73	595854	0.992	1.000	1.007	1.000	1.007	1.000	1.005	1.000	1.002	1.000	0.999	1.000	<i>1.604</i>	<i>1.232</i>	<i>1.348</i>	<i>1.300</i>
	937.54	2046181	0.997	1.000	0.987	1.000	0.992	1.000	1.000	1.000	0.997	1.000	0.999	1.000	0.506	0.321	<i>1.065</i>	<i>1.052</i>
	425.68	923780	1.018	1.000	1.010	1.000	1.009	1.000	1.013	1.000	1.014	1.000	1.021	1.000	<i>2.779</i>	<i>2.192</i>	<i>7.701</i>	<i>8.726</i>
iis-100-0-cov	629.92	103302	0.993	1.000	0.993	1.000	1.014	1.000	0.991	1.000	0.997	1.000	0.992	1.000	0.999	0.999	0.965	0.999
	545.20	92393	0.999	1.000	0.997	1.000	1.001	1.000	1.002	1.000	0.996	1.000	0.998	1.000	<i>1.128</i>	1.046	<i>1.053</i>	1.046
	520.78	81639	0.999	1.000	1.000	1.000	1.002	1.000	1.001	1.000	1.000	1.000	0.997	1.000	<i>1.151</i>	<i>1.128</i>	<i>1.097</i>	<i>1.128</i>
	506.53	84800	1.002	1.000	0.997	1.000	0.995	1.000	0.996	1.000	0.998	1.000	0.998	1.000	<i>1.117</i>	<i>1.080</i>	<i>1.077</i>	<i>1.080</i>
	544.56	92313	0.996	1.000	0.999	1.000	1.004	1.000	1.001	1.000	1.002	1.000	0.998	1.000	<i>1.089</i>	<i>1.052</i>	0.990	<i>1.052</i>
iis-bupa-cov	1915.72	157619	1.001	1.000	1.009	1.000	1.002	1.000	1.000	1.000	1.007	1.000	1.003	1.000	<i>1.704</i>	<i>1.376</i>	<i>1.344</i>	<i>1.376</i>
	1944.83	164079	0.997	1.000	0.995	1.000	0.997	1.000	0.996	1.000	0.994	1.000	0.995	1.000	<i>1.259</i>	<i>1.099</i>	<i>1.117</i>	<i>1.099</i>
	1881.83	156888	0.998	1.000	0.999	1.000	0.993	1.000	0.998	1.000	0.996	1.000	0.996	1.000	<i>1.189</i>	<i>1.093</i>	<i>1.081</i>	<i>1.093</i>
	1959.19	161969	0.989	1.000	1.005	1.000	0.996	1.000	0.996	1.000	0.994	1.000	0.998	1.000	<i>1.398</i>	<i>1.234</i>	<i>1.193</i>	<i>1.234</i>
	1820.52	158284	0.990	1.000	0.997	1.000	0.994	1.000	0.995	1.000	0.995	1.000	0.994	1.000	<i>1.378</i>	<i>1.219</i>	<i>1.241</i>	<i>1.219</i>
iis-pima-cov	293.79	4824	0.995	1.000	0.997	1.000	1.002	1.000	1.002	1.000	0.993	1.000	0.997	1.000	<i>1.072</i>	<i>1.109</i>	1.016	<i>1.109</i>
	437.19	12189	0.995	1.000	0.997	1.000	0.994	1.000	1.001	1.000	1.003	1.000	0.999	1.000	0.746	0.445	0.712	0.445

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Instance	default		degeneracy		dualbound		leaves		obj		nsols		sblps		nochecks		onlyroot		
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	246.99	4668	1.000	1.000	1.001	1.000	1.004	1.000	1.006	1.000	1.005	1.000	1.004	1.000	<i>1.326</i>	<i>1.583</i>	<i>1.214</i>	<i>1.583</i>	
	284.88	6607	1.002	1.000	1.003	1.000	1.000	1.000	1.001	1.000	0.996	1.000	0.998	1.000	1.225	<i>1.265</i>	<i>1.144</i>	<i>1.265</i>	
	556.78	17821	1.003	1.000	0.998	1.000	1.000	1.000	0.999	1.000	0.999	1.000	0.995	1.000	0.594	0.343	0.562	0.343	
i152lav	5.51	23	0.994	1.000	0.989	1.000	0.994	1.000	0.994	1.000	0.995	1.000	1.005	1.000	<i>2.278</i>	<i>1.520</i>	1.035	<i>1.244</i>	
	1.67	31	0.985	1.000	0.993	1.000	0.985	1.000	0.993	1.000	0.989	1.000	0.966	1.000	<i>2.131</i>	<i>1.122</i>	1.225	<i>1.183</i>	
	2.93	50	1.000	1.000	0.995	1.000	0.992	1.000	0.992	1.000	1.000	1.000	1.008	1.000	<i>3.046</i>	<i>1.367</i>	0.962	0.967	
	2.34	20	0.985	1.000	0.994	1.000	0.991	1.000	0.991	1.000	0.985	1.000	1.003	1.000	<i>3.713</i>	<i>2.008</i>	<i>1.275</i>	<i>1.342</i>	
	3.02	52	0.995	1.000	1.000	1.000	0.995	1.000	0.993	1.000	0.998	1.000	1.002	1.000	<i>2.167</i>	<i>1.204</i>	0.891	0.921	
lectsched-4-obj	27.04	805	0.753	0.215	<i>1.223</i>	0.740	1.004	1.000	1.009	0.924	1.005	1.000	0.730	0.314	0.748	0.215	0.978	<i>1.608</i>	
	23.16	868	<i>1.201</i>	0.288	0.813	0.525	1.029	<i>1.080</i>	0.887	0.765	0.988	1.000	0.666	0.311	<i>1.201</i>	0.288	0.995	<i>1.282</i>	
	86.08	1061	0.288	0.264	0.416	0.216	0.627	0.461	1.020	1.006	0.385	0.696	0.458	0.146	0.265	0.121	0.384	0.696	
	26.83	619	0.327	0.082	0.768	0.367	0.928	0.540	0.926	0.772	0.257	0.082	<i>2.333</i>	0.477	0.330	0.082	0.257	0.082	
22.73	745	0.909	0.253	1.038	0.805	1.005	1.000	0.992	1.000	0.954	1.004	1.000	<i>1.484</i>	0.910	0.913	0.253	0.701	0.647	
lseu	0.75	268	1.011	1.000	1.011	1.000	1.006	1.000	1.000	1.000	1.011	1.000	1.034	1.000	<i>1.566</i>	<i>1.095</i>	1.006	0.986	
	0.50	4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.010	1.000	1.000	
	0.51	205	0.993	1.000	1.000	1.000	0.993	1.000	0.993	1.000	0.993	1.000	1.000	1.000	<i>1.238</i>	0.866	0.993	0.931	
	0.50	91	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.738	1.000	0.969	
	0.50	191	1.007	1.000	1.000	1.000	1.000	1.000	1.007	1.000	1.007	1.000	1.007	1.000	<i>1.380</i>	0.670	1.000	0.680	
m100n500k4r1	3600.00	2166065	1.000	<i>1.118</i>	1.000	0.786	1.000	0.998	1.000	1.001	1.000	1.001	1.000	0.777	1.000	0.780	1.000	<i>1.171</i>	
	3600.00	2266017	1.000	1.035	1.000	0.712	1.000	0.995	1.000	0.999	1.000	0.998	1.000	0.701	1.000	0.782	1.000	<i>1.059</i>	
	3600.00	2611447	1.000	0.884	1.000	0.646	1.000	0.998	1.000	1.002	1.000	1.001	1.000	0.640	1.000	0.559	1.000	0.930	
	3600.00	2305045	1.000	0.937	1.000	0.723	1.000	0.998	1.000	0.999	1.000	0.999	1.000	0.723	1.000	0.640	1.000	0.989	
	3600.00	2226238	1.000	0.833	1.000	0.733	1.000	0.991	1.000	0.999	1.000	0.997	1.000	0.732	1.000	0.645	1.000	0.923	
macrophage	125.50	5163	1.001	1.000	1.006	1.000	1.001	1.000	1.005	1.000	1.001	1.000	1.001	1.000	<i>1.774</i>	<i>1.158</i>	0.911	0.701	
	157.18	7241	0.999	1.000	0.999	1.000	0.998	1.000	1.000	1.000	0.999	1.000	0.998	1.000	<i>1.535</i>	<i>1.184</i>	0.948	0.852	
	209.11	9131	1.000	1.000	0.999	1.000	1.002	1.000	0.998	1.000	0.999	1.000	0.999	1.000	<i>1.438</i>	<i>1.250</i>	0.821	<i>1.053</i>	
	162.53	7927	1.000	1.000	1.002	1.000	1.002	1.000	1.000	1.000	0.998	1.000	1.000	1.000	<i>1.876</i>	<i>1.088</i>	<i>1.083</i>	0.840	
	121.37	5239	0.999	1.000	0.997	1.000	0.998	1.000	1.000	1.000	1.001	1.000	0.997	1.000	<i>1.987</i>	<i>1.355</i>	<i>1.059</i>	<i>1.071</i>	
manna81	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.007	1.000	1.020	1.000	
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.013	1.000	1.013	1.000	
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.013	1.000	1.033	1.000	
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.013	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.007	1.000	1.033	1.000	
markshare1	3600.00	19010451	1.000	0.931	1.000	0.786	1.000	0.996	1.000	1.000	1.000	0.996	1.000	0.797	1.000	0.924	1.000	<i>1.083</i>	
	3600.00	20192578	1.000	0.862	1.000	0.893	1.000	0.999	1.000	0.997	1.000	1.000	1.000	0.890	1.000	0.856	1.000	1.017	
	3600.00	19529435	1.000	0.919	1.000	0.907	1.000	1.000	1.000	0.998	1.000	0.997	1.000	0.919	1.000	0.918	1.000	<i>1.219</i>	
	3600.00	20381558	1.000	0.898	1.000	0.865	1.000	0.998	1.000	1.001	1.000	1.002	1.000	0.818	1.000	0.903	1.000	1.017	
	3600.00	21608999	1.000	0.797	1.000	0.808	1.000	1.004	1.000	1.000	1.000	0.996	1.000	0.806	1.000	0.795	1.000	<i>1.090</i>	
markshare2	3600.00	4050504	1.000	0.843	1.000	<i>1.137</i>	1.000	0.995	1.000	0.991	1.000	0.995	1.000	<i>1.143</i>	1.000	0.846	1.000	0.958	

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sbtps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	3600.00	5646401	1.000	0.697	1.000	0.783	1.000	1.001	1.000	1.000	1.000	1.000	1.000	0.787	1.000	0.697	1.000	0.636
	3600.00	3589038	1.000	1.026	1.000	1.002	1.000	1.002	1.000	0.996	1.000	0.998	1.000	1.002	1.000	1.026	1.000	<i>1.083</i>
	3600.00	4244067	1.000	<i>1.069</i>	1.000	<i>1.098</i>	1.000	1.001	1.000	1.003	1.000	1.001	1.000	<i>1.106</i>	1.000	<i>1.069</i>	1.000	0.891
	3600.00	5150867	1.000	0.830	1.000	0.737	1.000	1.002	1.000	0.996	1.000	0.999	1.000	0.736	1.000	0.832	1.000	0.948
mcsched	285.92	13689	0.999	1.000	0.997	1.000	0.998	1.000	1.012	1.000	0.998	1.000	1.000	1.000	<i>1.093</i>	0.678	0.820	0.732
	271.88	11373	0.999	1.000	0.998	1.000	1.002	1.000	0.999	1.000	1.001	1.000	1.000	1.000	<i>3.196</i>	<i>1.747</i>	<i>1.459</i>	<i>1.710</i>
	233.97	10059	0.996	1.000	0.997	1.000	1.005	1.000	0.998	1.000	0.997	1.000	1.001	1.000	<i>2.468</i>	<i>1.296</i>	<i>1.287</i>	<i>1.310</i>
	286.25	12496	0.997	1.000	0.998	1.000	0.995	1.000	0.998	1.000	0.998	1.000	0.997	1.000	<i>2.450</i>	<i>1.245</i>	<i>1.055</i>	<i>1.146</i>
	270.69	10373	1.005	1.000	1.000	1.000	1.005	1.000	1.000	1.000	1.001	1.000	1.001	1.000	<i>1.542</i>	0.996	1.007	0.992
mine-166-5	58.69	1569	0.995	1.000	0.995	1.000	0.997	1.000	0.993	1.000	1.020	1.000	1.001	1.000	0.776	1.022	0.851	<i>2.359</i>
	57.78	1191	0.990	1.000	0.992	1.000	0.996	1.000	0.990	1.000	0.990	1.000	0.991	1.000	0.920	0.930	1.110	0.901
	46.45	2244	1.001	1.000	1.004	1.000	1.006	1.000	1.007	1.000	1.001	1.000	1.003	1.000	<i>1.103</i>	<i>1.067</i>	<i>1.132</i>	0.650
	64.93	139	1.006	1.000	1.004	1.000	1.005	1.000	1.001	1.000	1.005	1.000	1.002	1.000	0.711	<i>5.397</i>	0.619	<i>6.515</i>
	42.28	2863	1.000	1.000	1.000	1.000	1.001	1.000	1.000	1.000	1.001	1.000	0.998	1.000	<i>1.165</i>	0.555	0.994	0.873
mine-90-10	276.07	51926	1.002	1.000	1.001	1.000	<i>1.157</i>	<i>1.090</i>	0.999	1.000	1.000	1.000	1.003	1.000	1.033	0.750	0.767	0.596
	125.32	22195	0.998	1.000	1.005	1.000	0.998	1.000	0.999	1.000	1.003	1.000	1.001	1.000	<i>4.652</i>	<i>3.660</i>	<i>1.749</i>	<i>1.438</i>
	173.25	25979	1.001	1.000	1.004	1.000	0.999	1.000	0.999	1.000	1.004	1.000	0.999	1.000	<i>1.687</i>	<i>1.060</i>	<i>2.725</i>	<i>2.264</i>
	500.83	92879	1.003	1.000	1.000	1.000	<i>1.324</i>	<i>1.061</i>	0.999	1.000	0.999	1.000	0.999	1.000	0.809	0.459	0.556	0.457
	236.18	40409	1.005	1.000	1.003	1.000	0.907	<i>1.242</i>	1.004	1.000	1.002	1.000	1.013	1.000	<i>2.162</i>	<i>1.767</i>	0.762	0.592
misc03	1.39	398	1.004	1.000	1.004	1.000	1.000	1.000	1.013	1.000	1.004	1.000	0.983	1.000	0.799	0.267	0.711	0.263
	0.71	15	1.000	1.000	0.994	1.000	1.012	1.000	1.006	1.000	<i>1.076</i>	<i>1.226</i>	1.006	1.000	<i>1.427</i>	<i>1.226</i>	<i>1.094</i>	<i>1.226</i>
	0.70	19	1.018	1.000	0.994	1.000	1.006	1.000	1.018	1.000	<i>1.165</i>	<i>1.487</i>	0.976	1.000	<i>1.512</i>	<i>1.471</i>	<i>1.176</i>	<i>1.487</i>
	1.00	111	0.990	1.000	1.010	1.000	1.010	1.000	1.000	1.000	0.985	1.000	1.000	1.000	1.015	0.763	0.855	0.706
	0.66	15	0.988	1.000	1.000	1.000	0.988	1.000	0.988	1.000	<i>1.187</i>	<i>1.609</i>	0.988	1.000	<i>1.608</i>	<i>1.435</i>	<i>1.151</i>	<i>1.609</i>
misc07	38.05	28289	1.006	1.000	1.027	1.000	0.998	1.000	0.998	1.000	<i>1.089</i>	<i>1.188</i>	1.000	1.000	<i>1.496</i>	0.758	<i>1.087</i>	<i>1.188</i>
	36.66	29782	0.995	1.000	0.996	1.000	0.998	1.000	0.999	1.000	1.001	1.000	1.004	1.000	<i>2.177</i>	1.017	0.946	<i>1.080</i>
	21.56	17632	0.995	1.000	0.993	1.000	0.998	1.000	1.004	1.000	1.001	1.000	0.993	1.000	<i>3.660</i>	<i>1.598</i>	<i>2.274</i>	<i>2.333</i>
	45.95	38975	0.997	1.000	0.994	1.000	0.996	1.000	1.004	1.000	1.005	1.000	1.005	1.000	<i>1.340</i>	0.588	0.812	0.806
	30.94	29476	0.988	1.000	1.001	1.000	0.998	1.000	0.990	1.000	<i>1.082</i>	0.937	0.994	1.000	<i>1.266</i>	0.557	<i>1.084</i>	0.937
mitre	10.20	1	<i>1.390</i>	1.000	0.996	1.000	1.012	1.000	<i>1.054</i>	1.000	0.991	1.000	<i>1.071</i>	1.000	<i>1.381</i>	1.000	<i>1.374</i>	<i>1.000</i>
	10.28	1	<i>1.469</i>	1.000	0.989	1.000	1.006	1.000	0.991	1.000	<i>1.481</i>	1.000	0.989	1.000	<i>1.449</i>	1.000	<i>1.456</i>	1.000
	10.94	1	<i>1.384</i>	1.000	0.955	1.000	0.961	1.000	0.946	1.000	<i>1.357</i>	1.000	0.955	1.000	<i>1.389</i>	1.000	<i>1.447</i>	1.000
	10.45	1	<i>1.412</i>	1.000	0.994	1.000	0.990	1.000	0.987	1.000	0.991	1.000	0.979	1.000	<i>1.397</i>	1.000	<i>1.400</i>	1.000
	13.12	1	1.019	1.000	0.996	1.000	0.984	1.000	0.982	1.000	1.008	1.000	0.994	1.000	1.046	1.000	<i>1.055</i>	1.000
mod008	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.54	2	0.994	1.000	1.006	1.000	1.000	1.000	0.994	1.000	0.994	1.000	1.000	1.000	1.026	1.000	1.032	1.000
	0.52	2	1.013	1.000	1.013	1.000	1.007	1.000	0.993	1.000	0.987	1.000	1.007	1.000	1.026	0.990	1.020	0.990
	0.52	1	0.993	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.020	1.000	1.033	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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mod010	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	<i>1.460</i>	1.000	<i>1.273</i>	1.000	
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	<i>1.193</i>	1.000	<i>1.180</i>	1.000	
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	<i>1.233</i>	1.010	<i>1.273</i>	1.010	
	0.52	2	1.007	1.000	1.020	1.000	0.993	1.000	0.993	1.000	0.993	1.000	1.007	1.000	1.007	1.000	<i>1.329</i>	1.000	<i>1.197</i>	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	<i>1.347</i>	1.010	<i>1.320</i>	1.010	
mzzv11	332.43	2022	0.999	1.000	1.000	1.000	0.995	1.000	1.005	1.000	0.995	1.000	0.996	1.000	<i>1.490</i>	0.583	0.932	0.330		
	229.41	959	1.002	1.000	0.999	1.000	1.001	1.000	1.005	1.000	1.002	1.000	1.003	1.000	<i>1.453</i>	0.818	<i>1.573</i>	<i>1.220</i>		
	310.05	1421	1.004	1.000	1.000	1.000	1.001	1.000	0.995	1.000	0.999	1.000	0.999	1.000	0.910	0.415	<i>1.175</i>	0.525		
	327.03	1579	0.987	1.000	1.001	1.000	0.995	1.000	0.995	1.000	0.994	1.000	0.993	1.000	1.000	0.378	0.964	0.392		
	186.14	627	1.000	1.000	1.003	1.000	1.003	1.000	1.008	1.000	1.007	1.000	1.007	1.000	<i>1.746</i>	0.791	<i>1.458</i>	0.770		
mzzv42z	152.40	265	0.992	1.000	0.996	1.000	0.999	1.000	0.993	1.000	0.991	1.000	0.999	1.000	<i>2.086</i>	<i>1.477</i>	0.984	0.753		
	131.25	125	0.999	1.000	0.993	1.000	0.993	1.000	0.983	1.000	0.992	1.000	<i>1.107</i>	<i>1.053</i>	<i>2.096</i>	<i>1.636</i>	<i>1.692</i>	<i>1.667</i>		
	197.62	200	1.006	1.000	1.003	1.000	1.006	1.000	1.005	1.000	1.002	1.000	1.016	0.923	<i>2.262</i>	<i>1.597</i>	<i>1.436</i>	<i>1.117</i>		
	213.83	456	1.002	1.000	1.001	1.000	1.001	1.000	1.006	1.000	0.996	1.000	0.945	0.736	<i>1.504</i>	0.845	<i>1.677</i>	0.968		
	167.65	300	0.999	1.000	0.998	1.000	0.998	1.000	1.000	1.000	1.007	1.000	1.003	1.000	<i>1.347</i>	0.657	<i>1.143</i>	0.695		
neos-1109824	37.52	1796	0.996	1.000	1.037	1.000	0.995	1.000	0.988	1.000	<i>1.572</i>	<i>2.657</i>	1.018	1.000	<i>2.154</i>	<i>2.246</i>	<i>1.553</i>	<i>2.657</i>		
	46.67	3438	0.998	1.000	1.027	<i>1.072</i>	0.996	1.000	0.998	1.000	0.971	0.962	0.782	0.594	<i>1.320</i>	0.810	0.969	0.962		
	35.16	1913	0.995	1.000	1.002	1.000	0.997	1.000	1.002	1.000	0.995	1.000	<i>1.079</i>	0.966	<i>1.478</i>	0.997	<i>1.373</i>	<i>1.906</i>		
	77.65	8290	0.996	1.000	1.001	1.000	0.997	1.000	1.000	1.000	0.693	0.534	1.000	1.000	0.984	0.445	0.695	0.534		
	39.64	2247	0.990	1.000	0.992	1.000	0.991	1.000	0.994	1.000	<i>1.121</i>	<i>1.077</i>	1.030	0.933	<i>1.926</i>	<i>1.546</i>	<i>1.120</i>	<i>1.077</i>		
neos-1337307	3600.00	299554	1.000	1.013	1.000	1.008	1.000	0.990	1.000	1.001	1.000	<i>1.175</i>	1.000	0.993	1.000	0.167	1.000	<i>1.142</i>		
	3600.00	268930	1.000	0.999	1.000	1.001	1.000	0.998	1.000	0.999	1.000	<i>1.085</i>	1.000	0.999	1.000	0.169	1.000	0.837		
	3600.00	350002	1.000	1.003	1.000	0.996	1.000	1.004	1.000	1.005	1.000	1.013	1.000	0.999	1.000	0.153	1.000	<i>1.101</i>		
	3600.00	300182	1.000	1.003	1.000	0.998	1.000	0.999	1.000	1.003	1.000	<i>1.136</i>	1.000	0.998	1.000	0.152	1.000	<i>1.124</i>		
	3600.00	367948	1.000	1.015	1.000	1.008	1.000	1.001	1.000	1.005	1.000	0.749	0.176	1.000	1.004	1.000	0.112	1.000	0.986	
neos-1601936	2034.60	1453	0.999	1.000	<i>1.714</i>	<i>3.615</i>	0.998	1.000	0.999	1.000	<i>1.769</i>	0.679	1.002	1.000	<i>1.769</i>	<i>1.201</i>	<i>1.769</i>	0.679		
	3600.00	2861	1.000	1.004	1.000	1.039	1.000	1.004	1.000	0.997	1.000	0.393	1.000	1.002	1.000	0.356	1.000	0.609		
	1348.55	2661	0.993	1.000	<i>2.668</i>	<i>5.411</i>	1.001	1.000	1.001	1.000	<i>2.668</i>	0.548	1.000	1.000	<i>2.668</i>	0.541	<i>2.668</i>	0.528		
	3600.00	6917	1.000	1.000	<i>1.168</i>	1.000	1.000	1.000	1.004	1.000	0.429	0.429	1.000	1.000	1.000	0.831	0.898	0.158		
	3600.00	6139	1.000	1.000	1.000	0.686	1.000	1.000	1.000	1.000	0.419	0.176	1.000	1.000	1.000	0.441	0.417	0.176		
neos-686190	83.42	4906	0.998	1.000	0.998	1.000	0.992	1.000	0.998	1.000	1.001	1.000	1.000	1.000	<i>7.579</i>	<i>3.397</i>	<i>1.703</i>	<i>2.367</i>		
	86.19	6047	1.004	1.000	1.001	1.000	1.000	1.000	0.999	1.000	1.001	1.000	0.999	1.000	<i>8.670</i>	<i>3.407</i>	<i>4.366</i>	<i>6.493</i>		
	114.74	9156	1.005	1.000	1.000	1.000	0.999	1.000	0.998	1.000	0.999	1.000	1.001	1.000	<i>3.742</i>	0.651	0.736	0.632		
	116.53	9998	1.006	1.000	1.005	1.000	1.006	1.000	1.000	1.000	0.999	1.000	1.004	1.000	<i>3.255</i>	0.460	0.681	0.564		
	121.04	9806	0.998	1.000	1.002	1.000	0.999	1.000	0.998	1.000	1.004	1.000	0.997	1.000	<i>2.484</i>	0.493	0.627	0.572		
neos-849702	114.99	1680	<i>1.802</i>	0.595	0.862	0.835	0.866	0.835	<i>1.801</i>	0.595	<i>1.802</i>	0.595	<i>1.731</i>	<i>4.759</i>	<i>1.802</i>	0.595	<i>9.601</i>	<i>11.858</i>		
	353.12	77703	<i>2.900</i>	0.364	<i>2.216</i>	<i>4.411</i>	<i>2.214</i>	<i>4.411</i>	<i>2.910</i>	0.364	<i>2.907</i>	0.364	<i>9.463</i>	<i>19.062</i>	<i>2.919</i>	0.364	<i>2.830</i>	<i>2.084</i>		
	357.57	9988	<i>2.795</i>	0.359	0.511	0.342	0.514	0.342	<i>2.802</i>	0.359	<i>2.797</i>	0.359	<i>2.369</i>	<i>2.377</i>	<i>2.799</i>	0.359	<i>2.111</i>	0.080		
	261.49	16745	1.021	0.048	<i>1.101</i>	1.032	<i>1.100</i>	1.032	1.019	0.048	1.016	0.048	<i>1.557</i>	<i>1.159</i>	1.023	0.048	<i>5.019</i>	<i>1.101</i>		

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sbtps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	143.57	25014	<i>1.981</i>	0.335	<i>2.290</i>	<i>4.955</i>	<i>2.283</i>	<i>4.955</i>	<i>1.981</i>	0.335	<i>1.985</i>	0.335	<i>6.512</i>	<i>16.346</i>	<i>1.980</i>	0.335	<i>5.285</i>	<i>5.390</i>
neos-934278	3600.00	1175	1.000	0.993	1.000	0.991	1.000	0.993	1.000	0.993	1.000	0.993	1.000	1.000	1.000	0.335	1.000	0.340
	3600.00	267	1.000	1.005	1.000	1.005	1.000	1.005	1.000	1.005	1.000	1.014	1.000	1.005	1.000	<i>1.101</i>	1.000	<i>1.153</i>
	3600.00	266	1.000	1.000	1.000	1.003	1.000	1.008	1.000	0.989	1.000	1.000	1.000	1.008	1.000	<i>1.124</i>	1.000	<i>1.182</i>
	3600.00	399	1.000	1.020	1.000	0.953	1.000	1.016	1.000	1.014	1.000	1.014	1.000	1.012	1.000	0.835	1.000	0.857
	3600.00	523	1.000	1.002	1.000	0.998	1.000	1.003	1.000	1.000	1.000	1.003	1.000	1.000	1.000	0.680	1.000	0.717
neos18	24.17	1378	0.363	0.121	0.993	1.000	0.993	1.000	0.981	1.047	0.997	1.000	0.575	0.287	0.354	0.121	0.915	0.918
	21.26	1604	<i>1.162</i>	0.653	<i>1.403</i>	<i>1.457</i>	1.028	<i>1.199</i>	0.996	1.000	1.000	1.000	<i>1.429</i>	<i>1.072</i>	0.967	0.467	1.031	<i>1.431</i>
	23.36	1646	<i>1.229</i>	0.684	0.993	1.000	0.994	1.000	0.998	1.000	0.995	1.000	0.840	0.248	<i>1.218</i>	0.684	0.914	0.824
	19.21	996	0.812	0.443	0.840	0.849	0.997	1.000	0.997	1.000	1.021	1.000	0.789	0.366	0.810	0.443	<i>1.059</i>	<i>1.091</i>
	22.07	1049	0.987	0.925	0.855	0.634	1.004	1.000	1.001	1.000	0.997	1.000	0.906	0.657	0.948	0.795	<i>1.174</i>	<i>2.047</i>
ns1208400	2439.01	780	0.385	0.219	0.396	0.178	0.146	0.062	0.994	1.000	0.485	0.271	0.296	0.090	0.485	0.271	0.482	0.404
	1985.63	5751	<i>1.378</i>	<i>1.450</i>	0.948	0.886	<i>1.673</i>	0.733	1.003	1.000	<i>1.395</i>	<i>1.451</i>	0.415	0.213	<i>1.390</i>	<i>1.450</i>	0.486	0.380
	1467.85	1351	0.363	0.355	0.810	0.504	0.415	0.283	1.000	1.000	0.368	0.355	0.713	0.156	0.367	0.355	0.673	0.768
	3600.00	2617	0.071	0.122	0.493	<i>1.157</i>	0.274	0.476	0.309	0.607	0.070	0.122	0.244	0.332	0.071	0.122	0.147	0.400
	2388.79	3984	0.551	0.313	0.915	<i>1.198</i>	0.649	0.464	0.999	1.000	0.054	0.069	0.434	0.229	0.051	0.068	0.533	0.656
ns1688347	55.09	818	0.939	0.975	0.998	1.013	<i>1.209</i>	<i>1.666</i>	<i>1.084</i>	<i>1.283</i>	1.040	0.935	1.000	1.000	0.999	<i>1.103</i>	1.038	0.935
	45.64	422	0.931	0.518	0.996	1.000	<i>1.062</i>	0.892	0.986	0.969	<i>1.391</i>	<i>1.591</i>	0.998	1.000	<i>1.058</i>	0.839	<i>1.396</i>	<i>1.591</i>
	106.90	1690	<i>1.509</i>	<i>1.626</i>	1.000	1.000	0.999	0.911	<i>1.152</i>	0.855	<i>1.478</i>	<i>1.240</i>	1.001	1.000	0.884	0.571	<i>1.492</i>	<i>1.240</i>
	139.57	1219	0.957	1.024	1.018	<i>1.095</i>	0.994	1.000	0.945	<i>1.088</i>	<i>1.130</i>	0.999	0.998	1.000	0.682	0.329	0.771	0.500
	55.82	414	0.924	0.591	0.999	1.000	0.719	0.608	0.996	1.000	<i>1.169</i>	<i>1.244</i>	1.002	1.000	0.850	0.550	<i>1.169</i>	<i>1.244</i>
ns1830653	132.81	5720	1.002	1.000	1.000	1.000	0.810	0.829	1.001	1.000	<i>1.130</i>	1.028	0.998	1.000	<i>1.142</i>	0.663	<i>1.132</i>	1.028
	123.49	5512	1.003	1.000	1.002	1.000	<i>1.248</i>	<i>1.054</i>	1.001	1.000	<i>1.221</i>	<i>1.285</i>	1.003	1.000	<i>1.548</i>	<i>1.133</i>	<i>1.223</i>	<i>1.285</i>
	161.13	10467	0.999	1.000	1.002	1.000	0.953	<i>1.090</i>	1.000	1.000	<i>1.078</i>	0.985	0.803	0.886	<i>1.229</i>	0.479	<i>1.093</i>	0.985
	143.05	7519	1.001	1.000	0.826	0.713	<i>1.065</i>	1.011	0.999	1.000	<i>1.108</i>	<i>1.177</i>	0.785	0.589	<i>1.193</i>	0.833	<i>1.104</i>	<i>1.177</i>
	146.20	5836	0.999	1.000	0.999	1.000	0.779	0.639	0.999	1.000	<i>1.158</i>	0.738	0.851	0.746	1.028	0.406	<i>1.162</i>	0.738
nsrand-ixp	422.05	50124	0.995	1.000	1.011	1.000	0.999	1.000	0.996	1.000	1.002	1.000	<i>1.302</i>	0.946	<i>6.327</i>	0.938	<i>1.897</i>	<i>1.892</i>
	643.65	86869	0.992	1.000	1.002	1.000	0.996	1.000	0.998	1.000	0.996	1.000	<i>1.275</i>	0.923	<i>4.263</i>	0.891	0.503	0.378
	568.28	56575	1.002	1.000	1.011	1.000	1.001	1.000	1.000	1.000	1.002	1.000	<i>1.063</i>	0.996	<i>6.326</i>	0.715	<i>1.101</i>	1.016
	582.50	61056	1.000	1.000	0.998	1.000	1.001	1.000	1.003	1.000	1.008	1.000	<i>2.283</i>	0.885	<i>5.237</i>	<i>1.122</i>	0.898	0.893
	367.03	38012	0.991	1.000	0.995	1.000	0.993	1.000	0.999	1.000	0.995	1.000	<i>1.142</i>	1.032	<i>9.405</i>	<i>1.958</i>	<i>1.867</i>	<i>2.088</i>
opt1217	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p0033	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Instance	default		degeneracy		dualbound		leaves		obj		nsols		sblps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p0201	0.55	5	0.994	1.000	1.006	1.000	0.987	1.000	1.000	1.000	0.981	1.000	1.000	1.000	0.968	<i>1.057</i>	0.968	<i>1.057</i>
	0.71	9	1.018	1.000	1.006	1.000	1.012	1.000	1.012	1.000	1.000	1.000	1.023	1.000	0.924	0.982	0.924	0.982
	1.59	5	1.019	1.000	1.008	1.000	1.000	1.000	1.000	1.000	1.015	1.000	1.023	1.000	0.749	<i>1.210</i>	0.819	<i>2.419</i>
	0.90	13	1.000	1.000	0.995	1.000	1.011	1.000	1.005	1.000	1.005	1.000	0.989	1.000	<i>1.058</i>	<i>1.088</i>	0.911	<i>1.088</i>
	0.91	59	0.990	1.000	0.990	1.000	1.000	1.000	0.990	1.000	0.995	1.000	0.995	1.000	0.890	0.761	0.812	0.761
p0282	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	3	1.000	1.000	1.000	1.000	1.000	1.000	1.007	1.000	1.000	1.000	1.013	1.000	1.000	0.990	1.033	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p0548	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p2756	2.46	5	1.014	1.000	1.014	1.000	1.000	1.000	1.006	1.000	1.012	1.000	1.014	1.000	0.942	<i>1.067</i>	0.861	0.990
	3.33	5	1.000	1.000	1.005	1.000	1.005	1.000	1.005	1.000	1.002	1.000	1.012	1.000	<i>1.102</i>	1.010	0.998	0.990
	2.16	3	0.991	1.000	0.987	1.000	0.994	1.000	0.981	1.000	0.991	1.000	0.978	1.000	<i>1.073</i>	1.010	0.981	1.000
	2.60	3	0.983	1.000	0.994	1.000	0.994	1.000	0.983	1.000	0.983	1.000	0.978	1.000	0.969	1.010	0.964	1.019
	1.22	2	1.027	1.000	1.041	1.000	1.023	1.000	1.027	1.000	1.023	1.000	1.014	1.000	<i>1.077</i>	1.010	<i>1.063</i>	1.010
protfold	3600.00	4825	1.000	0.685	1.000	1.007	1.000	1.009	1.000	0.990	1.000	1.008	1.000	1.002	1.000	0.575	1.000	0.530
	3600.00	8262	1.000	0.315	1.000	1.001	1.000	1.011	1.000	0.994	1.000	0.997	1.000	1.001	1.000	0.303	1.000	0.289
	3600.00	5818	1.000	0.481	1.000	0.999	1.000	0.997	1.000	0.999	1.000	0.995	1.000	0.998	1.000	0.558	1.000	0.358
	3600.00	7269	1.000	0.262	1.000	1.002	1.000	1.001	1.000	1.001	1.000	1.006	1.000	1.001	1.000	0.264	1.000	0.231
	3600.00	4748	1.000	0.344	1.000	0.998	1.000	0.848	1.000	1.000	1.000	1.000	1.003	1.000	0.415	1.000	0.299	
pw-myciel4	3600.00	519342	1.000	0.695	1.000	0.895	1.000	0.999	0.662	0.587	1.000	1.000	1.000	0.858	1.000	<i>1.087</i>	1.000	0.868
	3600.00	442617	1.000	0.826	0.800	0.789	1.000	0.999	0.932	0.954	1.000	1.000	1.000	0.858	1.000	0.636	1.000	1.040
	3600.00	389396	1.000	0.826	1.000	<i>1.146</i>	1.000	0.994	1.000	0.974	1.000	0.992	1.000	<i>1.053</i>	1.000	0.780	1.000	0.910
	2920.77	395762	<i>1.232</i>	0.905	<i>1.232</i>	0.938	1.006	1.000	<i>1.232</i>	0.872	1.000	1.000	<i>1.232</i>	0.943	<i>1.232</i>	<i>1.125</i>	<i>1.232</i>	0.984
	3600.00	405310	0.848	0.934	1.000	0.991	1.000	1.000	0.939	1.044	1.000	1.001	1.000	1.031	0.971	0.834	1.000	<i>1.204</i>
qnet1	4.52	33	1.004	1.000	1.005	1.000	1.013	1.000	0.998	1.000	1.005	1.000	1.007	1.000	0.455	0.797	0.455	0.797
	3.09	3	1.007	1.000	1.005	1.000	1.005	1.000	1.010	1.000	1.010	1.000	0.998	1.000	<i>1.086</i>	0.990	0.804	1.000
	3.94	29	0.996	1.000	1.002	1.000	0.994	1.000	1.004	1.000	1.000	1.000	1.002	1.000	<i>1.138</i>	1.000	0.949	1.000
	2.23	3	1.009	1.000	1.000	1.000	1.006	1.000	1.003	1.000	1.009	1.000	1.000	1.000	<i>1.161</i>	<i>1.087</i>	<i>1.071</i>	1.010
	3.69	34	1.004	1.000	0.989	1.000	0.998	1.000	0.994	1.000	0.989	1.000	1.000	1.000	<i>1.198</i>	0.970	0.887	1.022
qnet1_o	3.93	27	0.988	1.000	0.992	1.000	0.996	1.000	1.002	1.000	0.996	1.000	0.988	1.000	0.919	0.929	0.836	0.929
	3.35	24	1.007	1.000	1.005	1.000	1.000	1.000	1.002	1.000	0.998	1.000	1.009	1.000	<i>1.094</i>	0.992	0.897	0.992

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sblps		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	3.37	15	1.005	1.000	1.009	1.000	0.995	1.000	1.011	1.000	1.014	1.000	1.002	1.000	0.712	0.904	0.616	0.887
	1.66	2	1.004	1.000	0.996	1.000	1.000	1.000	0.992	1.000	1.004	1.000	1.008	1.000	<i>1.143</i>	1.000	0.996	1.000
	1.83	3	1.004	1.000	1.007	1.000	1.007	1.000	1.000	1.000	1.007	1.000	1.004	1.000	<i>1.085</i>	1.000	1.018	1.000
reblock67	222.59	49530	1.002	1.000	0.999	1.000	1.007	1.000	0.999	1.000	0.997	1.000	0.995	1.000	<i>2.701</i>	<i>1.225</i>	0.803	0.598
	161.89	40625	1.000	1.000	0.997	1.000	1.000	1.000	0.996	1.000	0.998	1.000	1.000	1.000	<i>2.270</i>	0.943	<i>1.272</i>	<i>1.214</i>
	194.41	42542	1.001	1.000	1.002	1.000	0.857	0.853	0.997	1.000	1.003	1.000	1.001	1.000	<i>2.191</i>	0.951	0.902	0.876
	199.06	52613	1.006	1.000	1.003	1.000	0.992	1.032	1.006	1.000	1.005	1.000	1.001	1.000	<i>3.355</i>	<i>1.638</i>	0.868	0.767
	239.84	57566	0.997	1.000	0.997	1.000	0.994	1.000	0.997	1.000	0.996	1.000	0.997	1.000	<i>1.707</i>	<i>1.170</i>	0.716	0.795
rmine6	971.86	111047	1.000	1.000	1.006	1.000	1.002	1.000	1.000	1.000	1.001	1.000	0.999	1.000	<i>1.724</i>	<i>1.068</i>	<i>1.441</i>	0.906
	883.48	89213	0.999	1.000	1.000	1.000	0.990	1.000	0.999	1.000	1.002	1.000	1.002	1.000	<i>2.249</i>	<i>1.574</i>	0.945	0.921
	775.32	91530	1.002	1.000	1.002	1.000	1.000	1.000	1.001	1.000	1.002	1.000	1.000	1.000	<i>2.090</i>	<i>1.268</i>	1.037	1.014
	740.58	85429	1.002	1.000	1.000	1.000	0.999	1.000	1.005	1.000	0.999	1.000	0.992	1.000	<i>1.817</i>	<i>1.249</i>	<i>1.310</i>	<i>1.072</i>
	771.48	76017	1.002	1.000	1.001	1.000	1.002	1.000	1.001	1.000	0.998	1.000	1.001	1.000	<i>1.581</i>	<i>1.168</i>	<i>1.134</i>	<i>1.144</i>
rococoC10-001000	601.83	46983	1.003	1.000	1.000	1.000	0.998	1.000	0.998	1.000	0.998	1.000	1.000	1.000	<i>2.365</i>	<i>1.898</i>	<i>2.192</i>	<i>1.817</i>
	833.40	75156	1.003	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.002	1.000	<i>2.401</i>	<i>1.509</i>	<i>1.679</i>	<i>1.377</i>
	517.62	37178	0.998	1.000	1.002	1.000	1.003	1.000	<i>1.092</i>	<i>1.105</i>	1.002	1.000	1.001	1.000	<i>1.872</i>	<i>1.710</i>	<i>1.428</i>	<i>1.458</i>
	892.04	51410	1.001	1.000	1.002	1.000	0.999	1.000	1.001	1.000	1.003	1.000	1.003	1.000	<i>1.737</i>	<i>1.994</i>	<i>1.076</i>	<i>1.344</i>
	1047.39	66016	1.001	1.000	1.000	1.000	1.001	1.000	1.001	1.000	1.003	1.000	1.003	1.000	<i>2.255</i>	<i>1.863</i>	<i>1.367</i>	<i>1.434</i>
seymour	3600.00	102303	1.000	0.996	1.000	0.993	1.000	0.997	1.000	0.999	1.000	0.997	1.000	1.001	1.000	0.717	1.000	0.768
	3600.00	120875	1.000	0.999	1.000	1.001	1.000	1.005	1.000	0.997	1.000	1.005	1.000	1.001	1.000	0.626	1.000	0.656
	3600.00	123371	1.000	1.006	1.000	1.006	1.000	1.008	1.000	1.010	1.000	1.010	1.000	1.006	1.000	0.737	1.000	0.791
	3600.00	107935	1.000	1.005	1.000	1.003	1.000	1.004	1.000	1.003	1.000	1.002	1.000	1.011	1.000	0.836	1.000	0.943
	3600.00	97288	1.000	1.003	1.000	1.001	1.000	1.006	1.000	1.001	1.000	1.003	1.000	1.002	1.000	1.002	1.000	<i>1.069</i>
sp98ir	57.90	3948	1.003	1.000	1.009	1.000	1.003	1.000	1.020	1.000	1.010	1.000	1.008	1.000	<i>2.980</i>	<i>1.355</i>	<i>1.637</i>	<i>1.467</i>
	65.87	4178	1.001	1.000	1.003	1.000	1.003	1.000	1.003	1.000	1.004	1.000	1.007	1.000	<i>2.428</i>	<i>1.260</i>	<i>1.115</i>	<i>1.144</i>
	67.64	4735	1.004	1.000	1.002	1.000	1.001	1.000	1.003	1.000	1.001	1.000	1.008	1.000	<i>3.056</i>	<i>1.357</i>	<i>1.306</i>	<i>1.249</i>
	72.68	4603	0.997	1.000	1.002	1.000	1.003	1.000	0.999	1.000	1.001	1.000	1.005	1.000	<i>2.275</i>	0.892	0.890	0.882
	70.05	4780	0.997	1.000	0.997	1.000	0.995	1.000	0.999	1.000	1.005	1.000	1.004	1.000	<i>2.109</i>	<i>1.134</i>	<i>1.088</i>	<i>1.248</i>
stein27	1.12	2749	1.024	1.000	0.995	1.000	1.028	1.000	1.024	1.000	1.033	1.000	0.991	1.000	<i>1.491</i>	<i>1.081</i>	<i>1.094</i>	<i>1.081</i>
	1.19	2699	1.018	1.000	1.009	1.000	1.005	1.000	1.009	1.000	1.027	1.000	1.023	1.000	<i>1.502</i>	1.025	1.014	1.009
	1.25	2889	0.973	1.000	0.991	1.000	0.982	1.000	1.000	1.000	0.991	1.000	0.964	1.000	<i>1.382</i>	0.990	0.978	0.990
	1.14	2715	0.995	<i>1.056</i>	0.972	1.000	0.967	1.000	0.981	1.000	0.972	1.000	0.981	1.000	<i>1.486</i>	<i>1.056</i>	0.958	<i>1.056</i>
	1.13	2911	0.977	0.972	1.000	1.000	0.986	1.000	1.000	1.000	0.981	1.000	0.977	1.000	<i>1.394</i>	0.951	0.977	0.972
stein45	12.80	40723	0.985	0.962	0.995	1.000	0.981	1.000	0.986	1.000	0.979	1.000	0.981	1.000	<i>1.630</i>	0.971	0.964	0.916
	12.94	39012	0.968	0.995	0.996	1.000	0.984	1.000	0.972	1.000	0.989	1.000	0.972	1.000	<i>1.698</i>	0.966	0.935	0.976
	13.04	41930	1.000	0.985	0.999	1.000	0.988	1.000	0.994	1.000	0.999	1.000	1.006	1.000	<i>1.628</i>	0.931	0.994	0.975
	12.20	37543	1.022	1.015	0.993	1.000	1.001	1.000	0.994	1.000	0.992	1.000	0.992	1.000	<i>1.665</i>	<i>1.055</i>	1.047	1.015
	13.29	40503	0.981	1.006	0.994	1.000	0.978	1.000	0.992	1.000	0.992	1.000	0.999	1.000	<i>1.666</i>	0.984	0.985	1.006
tanglegram2	4.09	3	1.004	1.000	1.010	1.000	1.010	1.000	1.012	1.000	1.006	1.000	1.014	1.000	1.026	1.000	1.020	1.000

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Table 4: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy		dualbound		leaves		obj		nsols		sbips		nochecks		onlyroot	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	3.85	3	1.010	1.000	1.008	1.000	1.010	1.000	1.008	1.000	1.008	1.000	1.002	1.000	1.029	1.000	1.023	1.000
	4.25	3	0.990	1.000	1.000	1.000	0.998	1.000	1.008	1.000	1.008	1.000	1.008	1.000	1.011	1.000	1.023	1.000
	4.11	3	1.002	1.000	1.002	1.000	1.000	1.000	0.992	1.000	0.992	1.000	0.998	1.000	1.016	1.000	1.010	1.000
	4.23	3	0.994	1.000	1.000	1.000	0.985	1.000	0.990	1.000	0.998	1.000	0.994	1.000	1.010	1.000	1.011	1.000

Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	timeQ	nodesQ	timeQ	nodesQ	timeQ	nodesQ
10teams	2.14	1	<i>1.293</i>	1.000	1.022	1.000	<i>1.248</i>	1.000
	20.00	1367	0.244	0.072	<i>1.230</i>	1.001	0.246	0.072
	15.57	287	<i>1.636</i>	<i>2.729</i>	0.998	1.000	<i>1.508</i>	<i>1.835</i>
	4.16	5	<i>2.723</i>	<i>1.219</i>	1.006	1.000	<i>2.725</i>	<i>1.219</i>
	4.94	5	0.912	1.000	1.012	1.000	0.911	1.000
30n20b8	314.13	195	0.604	0.553	0.992	1.000	0.344	0.346
	157.33	71	0.711	0.596	1.000	1.000	0.808	0.596
	87.25	4	1.001	1.000	0.997	1.000	<i>1.193</i>	1.000
	213.06	102	<i>1.202</i>	<i>1.312</i>	0.976	0.950	1.048	0.782
	470.09	290	0.813	0.723	1.004	1.000	0.243	0.421
acc-tight5	125.35	802	<i>1.093</i>	<i>1.171</i>	0.426	0.302	<i>1.087</i>	<i>1.171</i>
	84.38	508	<i>1.786</i>	<i>2.650</i>	0.426	0.252	<i>1.790</i>	<i>2.650</i>
	50.45	195	0.974	0.929	<i>1.740</i>	<i>1.966</i>	0.978	0.929
	85.88	545	0.339	0.189	0.420	0.274	0.343	0.189
	73.38	627	0.418	0.161	<i>1.969</i>	<i>2.048</i>	0.418	0.161
air03	1.70	1	1.037	1.000	1.037	1.000	1.007	1.000
	1.71	1	1.004	1.000	1.007	1.000	1.004	1.000
	1.74	1	0.996	1.000	1.004	1.000	0.993	1.000
	1.75	1	1.000	1.000	0.993	1.000	1.002	1.000
	1.75	1	1.000	1.000	1.000	1.000	0.996	1.000
air04	49.46	110	1.015	1.000	1.003	1.000	1.007	1.000
	36.09	39	1.005	1.000	0.999	1.000	1.003	1.000
	52.88	118	0.997	1.000	0.999	1.000	0.989	1.000
	36.56	31	1.010	1.000	1.015	1.000	1.001	1.000
	48.35	122	0.998	1.000	1.007	1.000	1.001	1.000
air05	24.82	189	0.997	1.000	1.001	1.000	0.991	1.000
	26.54	239	1.004	1.000	1.001	1.000	1.009	1.000
	31.37	438	1.001	1.000	1.000	1.000	0.997	1.000
	27.36	283	1.005	1.000	1.004	1.000	1.010	1.000
	27.14	279	1.001	1.000	0.999	1.000	1.000	1.000
blend2	0.69	714	1.036	1.000	1.047	1.000	1.036	1.000
	1.08	973	0.995	1.000	1.010	1.000	1.010	1.000
	1.05	912	1.000	1.000	0.985	1.000	0.990	1.000
	0.67	543	0.982	1.000	1.000	1.000	1.006	1.000
	0.66	709	1.042	1.000	1.048	1.000	1.042	1.000
bley_xl1	164.49	1	1.009	1.000	1.000	1.000	1.007	1.000
	187.04	3	1.013	<i>1.146</i>	1.007	1.000	1.017	<i>1.146</i>
	182.51	13	0.887	0.903	1.006	1.000	0.896	0.903
	133.90	1	1.002	1.000	1.011	1.000	1.004	1.000
	135.56	1	1.012	1.000	1.008	1.000	1.007	1.000
bnatt350	378.09	3383	0.052	0.030	0.107	0.054	0.052	0.030
	521.76	4947	0.033	0.022	0.292	0.147	0.033	0.022
	397.10	4029	0.047	0.026	0.123	0.053	0.048	0.026
	155.46	1495	0.109	0.067	<i>2.608</i>	<i>2.974</i>	0.109	0.067

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	994.16	10057	0.044	0.021	0.330	0.259	0.044	0.021
cap6000	2.69	1830	1.011	1.000	1.011	1.000	0.997	1.000
	2.67	1837	0.995	1.000	0.995	1.000	1.000	1.000
	2.61	1959	0.994	1.000	1.017	1.000	1.014	1.000
	3.17	1924	1.005	1.000	1.000	1.000	0.998	1.000
	2.82	1762	1.008	1.000	1.005	1.000	0.997	1.000
cov1075	3600.00	1450527	0.991	<i>1.189</i>	1.000	0.996	0.991	<i>1.189</i>
	3600.00	1790225	1.000	0.974	1.000	1.002	1.000	0.978
	3600.00	1531529	1.000	<i>1.179</i>	1.000	1.000	1.000	<i>1.151</i>
	3600.00	1798178	1.000	0.984	1.000	1.008	1.000	0.984
	3600.00	1204894	1.000	<i>1.507</i>	1.000	0.998	1.000	<i>1.505</i>
csched010	3600.00	237077	1.000	0.961	1.000	0.963	0.812	0.726
	3600.00	202876	1.000	0.863	1.000	0.861	1.000	<i>1.145</i>
	2891.69	177527	<i>1.145</i>	<i>1.206</i>	<i>1.144</i>	<i>1.206</i>	<i>1.245</i>	<i>1.177</i>
	3600.00	238611	0.989	0.820	0.986	0.820	1.000	0.927
	3168.37	173932	<i>1.136</i>	<i>1.300</i>	<i>1.136</i>	<i>1.304</i>	<i>1.136</i>	<i>1.369</i>
eil33-2	69.44	583	1.013	1.000	1.007	1.000	1.006	1.000
	81.92	739	1.000	1.000	0.998	1.000	1.003	1.000
	84.87	847	1.004	1.000	1.005	1.000	1.001	1.000
	73.60	543	1.005	1.000	1.003	1.000	1.005	1.000
	70.01	583	1.001	1.000	1.001	1.000	0.999	1.000
eilB101	378.99	10582	1.002	1.000	1.015	1.000	0.993	1.000
	365.27	8427	0.994	1.000	0.994	1.000	0.996	1.000
	401.63	9358	1.004	1.000	0.996	1.000	1.004	1.000
	397.46	11465	1.000	1.000	1.000	1.000	1.001	1.000
	365.79	10006	1.005	1.000	0.997	1.000	0.999	1.000
enigma	0.50	809	1.000	0.825	1.000	0.998	1.000	0.542
	0.50	449	1.000	0.497	1.000	1.000	1.000	0.470
	0.50	541	1.000	0.254	1.000	0.977	1.000	0.237
	0.50	679	<i>1.060</i>	0.537	1.000	1.000	1.000	0.151
	0.50	445	1.000	0.543	1.000	1.006	1.033	0.543
enlight13	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
enlight14	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
fiber	1.00	2	1.005	1.000	1.025	1.000	1.005	1.000
	1.42	4	1.000	1.000	0.988	1.000	1.000	1.000

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	1.74	4	0.996	1.000	1.004	1.000	1.007	1.000
	1.53	4	1.000	1.000	1.008	1.000	1.000	1.000
	1.00	3	1.000	1.000	0.990	1.000	0.990	1.000
flugpl	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
gt2	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
harp2	691.56	1491878	1.008	1.000	0.999	1.000	1.005	1.000
	1159.66	2857677	0.998	1.000	0.998	1.000	0.997	1.000
	336.73	595854	0.999	1.000	1.006	1.000	0.999	1.000
	937.54	2046181	0.999	1.000	1.002	1.000	1.002	1.000
	425.68	923780	1.013	1.000	1.007	1.000	1.008	1.000
iis-100-0-cov	629.92	103302	0.998	1.000	1.021	1.000	0.992	1.000
	545.20	92393	0.995	1.000	0.997	1.000	1.001	1.000
	520.78	81639	1.001	1.000	1.000	1.000	1.000	1.000
	506.53	84800	0.999	1.000	0.995	1.000	1.000	1.000
	544.56	92313	1.007	1.000	1.003	1.000	1.004	1.000
iis-bupa-cov	1915.72	157619	1.000	1.000	1.003	1.000	1.001	1.000
	1944.83	164079	0.999	1.000	0.996	1.000	0.999	1.000
	1881.83	156888	0.991	1.000	0.992	1.000	1.008	1.000
	1959.19	161969	0.994	1.000	0.999	1.000	0.997	1.000
	1820.52	158284	0.994	1.000	0.993	1.000	1.014	1.000
iis-pima-cov	293.79	4824	1.004	1.000	0.999	1.000	0.999	1.000
	437.19	12189	1.007	1.000	1.001	1.000	1.013	1.000
	246.99	4668	1.002	1.000	1.000	1.000	1.002	1.000
	284.88	6607	1.002	1.000	1.000	1.000	1.003	1.000
	556.78	17821	0.997	1.000	0.997	1.000	1.001	1.000
l152lav	5.51	23	1.011	1.000	1.014	1.000	0.992	1.000
	1.67	31	0.989	1.000	0.993	1.000	1.000	1.000
	2.93	50	0.995	1.000	1.003	1.000	1.000	1.000
	2.34	20	0.985	1.000	0.994	1.000	0.991	1.000
	3.02	52	1.000	1.000	1.012	1.000	1.002	1.000
lectsched-4-obj	27.04	805	0.750	0.215	<i>1.052</i>	0.838	0.749	0.215
	23.16	796	<i>1.193</i>	0.288	1.008	0.823	<i>1.198</i>	0.288
	86.08	2419	0.285	0.206	0.626	0.461	0.265	0.121
	26.83	1231	0.327	0.082	0.933	0.540	0.331	0.082
	22.73	745	0.903	0.253	0.992	0.954	0.911	0.253

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
lseu	0.75	268	0.994	1.000	1.029	1.000	1.006	1.000
	0.50	4	1.000	1.000	1.000	1.000	1.000	1.000
	0.51	205	0.993	1.000	0.993	1.000	1.000	1.000
	0.50	91	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	191	1.000	1.000	1.000	1.000	1.000	1.000
m100n500k4r1	3600.00	2170459	1.000	<i>1.118</i>	1.000	1.002	1.000	0.781
	3600.00	2278212	1.000	1.035	1.000	0.996	1.000	0.783
	3600.00	2617105	1.000	0.884	1.000	1.000	1.000	0.560
	3600.00	2309660	1.000	0.935	1.000	0.998	1.000	0.638
	3600.00	2245563	1.000	0.834	1.000	0.996	1.000	0.647
macrophage	125.50	5163	1.000	1.000	1.006	1.000	1.001	1.000
	157.18	7241	0.998	1.000	0.998	1.000	0.999	1.000
	209.11	9131	1.000	1.000	1.000	1.000	1.001	1.000
	162.53	7927	0.998	1.000	1.000	1.000	1.002	1.000
	121.37	5239	0.995	1.000	0.996	1.000	0.997	1.000
manna81	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
markshare1	3600.00	19093205	1.000	0.927	1.000	0.997	1.000	0.924
	3600.00	20203360	1.000	0.859	1.000	0.998	1.000	0.856
	3600.00	19520584	1.000	0.919	1.000	0.999	1.000	0.918
	3600.00	20427204	1.000	0.901	1.000	1.000	1.000	0.903
	3600.00	21513467	1.000	0.795	1.000	1.000	1.000	0.796
markshare2	3600.00	4072360	1.000	0.843	1.000	0.995	1.000	0.847
	3600.00	5640455	1.000	0.699	1.000	1.000	1.000	0.699
	3600.00	3582521	1.000	1.025	1.000	0.998	1.000	1.023
	3600.00	4239467	1.000	<i>1.067</i>	1.000	1.006	1.000	<i>1.070</i>
	3600.00	5142521	1.000	0.828	1.000	1.004	1.000	0.836
mcsched	285.92	13689	0.999	1.000	1.000	1.000	0.997	1.000
	271.88	11373	0.999	1.000	0.999	1.000	1.001	1.000
	233.97	10059	1.003	1.000	0.995	1.000	1.000	1.000
	286.25	12496	0.995	1.000	1.000	1.000	0.997	1.000
	270.69	10373	1.004	1.000	0.999	1.000	1.000	1.000
mine-166-5	58.69	1569	0.995	1.000	1.001	1.000	0.998	1.000
	57.78	1191	0.993	1.000	0.994	1.000	0.992	1.000
	46.45	2244	0.997	1.000	1.004	1.000	1.005	1.000
	64.93	139	0.998	1.000	1.007	1.000	1.000	1.000
	42.28	2863	1.001	1.000	1.001	1.000	1.000	1.000
mine-90-10	276.07	47643	<i>1.162</i>	<i>1.090</i>	<i>1.162</i>	<i>1.090</i>	<i>1.157</i>	<i>1.090</i>
	125.32	22195	0.999	1.000	0.997	1.000	1.002	1.000
	173.25	25979	1.001	1.000	0.999	1.000	1.000	1.000
	500.83	87496	<i>1.322</i>	<i>1.061</i>	<i>1.321</i>	<i>1.061</i>	<i>1.322</i>	<i>1.061</i>

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	236.18	32520	0.907	<i>1.242</i>	0.908	<i>1.242</i>	0.904	<i>1.242</i>
misc03	1.39	398	1.008	1.000	0.996	1.000	0.992	1.000
	0.71	15	0.994	1.000	1.018	1.000	<i>1.094</i>	<i>1.226</i>
	0.70	19	1.006	1.000	1.006	1.000	<i>1.200</i>	<i>1.370</i>
	1.00	111	1.000	1.000	0.990	1.000	0.995	1.000
	0.66	15	1.018	1.000	0.994	1.000	<i>1.193</i>	<i>1.609</i>
misc07	38.05	28289	0.998	1.000	1.026	1.000	<i>1.090</i>	<i>1.188</i>
	36.66	29782	0.999	1.000	0.999	1.000	0.999	1.000
	21.56	17632	0.999	1.000	0.996	1.000	0.994	1.000
	45.95	38975	1.006	1.000	1.007	1.000	1.004	1.000
	30.94	29476	0.993	1.000	0.996	1.000	<i>1.088</i>	0.937
mitre	10.20	1	<i>1.376</i>	1.000	0.992	1.000	<i>1.354</i>	1.000
	10.28	1	<i>1.444</i>	1.000	1.009	1.000	<i>1.473</i>	1.000
	10.94	1	<i>1.380</i>	1.000	0.960	1.000	<i>1.391</i>	1.000
	10.45	1	<i>1.401</i>	1.000	0.994	1.000	<i>1.399</i>	1.000
	13.12	1	1.038	1.000	0.991	1.000	<i>1.051</i>	1.000
mod008	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.54	2	1.000	1.000	1.000	1.000	1.000	1.000
	0.52	2	1.000	1.000	0.993	1.000	1.000	1.000
	0.52	1	0.993	1.000	0.993	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
mod010	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.52	2	1.000	1.000	0.993	1.000	0.993	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
mzzv11	332.43	2022	0.999	1.000	0.994	1.000	1.000	1.000
	229.41	959	1.002	1.000	1.003	1.000	1.001	1.000
	310.05	1421	0.998	1.000	1.000	1.000	0.998	1.000
	327.03	1579	0.994	1.000	0.995	1.000	0.994	1.000
	186.14	627	1.001	1.000	1.002	1.000	1.000	1.000
mzzv42z	152.40	265	0.994	1.000	0.992	1.000	0.993	1.000
	131.25	125	0.993	1.000	0.993	1.000	<i>1.105</i>	<i>1.053</i>
	197.62	200	1.004	1.000	1.006	1.000	1.024	0.923
	213.83	456	0.999	1.000	1.001	1.000	0.933	0.736
	167.65	300	1.000	1.000	1.000	1.000	1.004	1.000
neos-1109824	37.52	1796	0.998	1.000	0.995	1.000	<i>1.662</i>	<i>2.859</i>
	46.67	3438	1.000	1.000	0.998	1.000	1.009	0.969
	35.16	1913	0.999	1.000	0.998	1.000	<i>1.088</i>	0.966
	77.65	8290	1.003	1.000	1.003	1.000	0.696	0.534
	39.64	2247	0.993	1.000	0.991	1.000	<i>1.156</i>	<i>1.084</i>
neos-1337307	3600.00	302483	1.000	1.004	1.000	1.006	1.000	<i>1.178</i>
	3600.00	269510	1.000	1.001	1.000	1.003	1.000	<i>1.084</i>

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	timeQ	nodesQ	timeQ	nodesQ	timeQ	nodesQ
	3600.00	348643	1.000	1.002	1.000	1.000	1.000	1.012
	3600.00	300587	1.000	1.011	1.000	0.993	1.000	<i>1.131</i>
	3600.00	367746	1.000	1.002	1.000	1.007	1.000	0.748
neos-1601936	2034.60	1453	0.996	1.000	1.009	1.000	<i>1.769</i>	<i>2.100</i>
	3600.00	2849	1.000	1.003	1.000	1.000	1.000	0.377
	1348.55	2661	1.000	1.000	1.000	1.000	<i>2.668</i>	0.581
	3600.00	6919	1.000	0.999	1.000	0.999	1.000	0.584
	3600.00	6139	1.000	1.000	1.000	1.010	0.993	0.519
neos-686190	83.42	4906	1.003	1.000	0.997	1.000	0.995	1.000
	86.19	6047	1.001	1.000	1.000	1.000	1.002	1.000
	114.74	9156	1.000	1.000	1.001	1.000	1.000	1.000
	116.53	9998	1.008	1.000	1.002	1.000	0.999	1.000
	121.04	9806	1.004	1.000	1.003	1.000	0.998	1.000
neos-849702	114.99	2031	<i>1.820</i>	0.595	<i>1.817</i>	0.595	<i>1.804</i>	0.595
	353.12	17540	<i>2.901</i>	0.364	<i>2.924</i>	0.364	<i>2.903</i>	0.364
	357.57	29405	<i>2.792</i>	0.359	<i>2.795</i>	0.359	<i>2.803</i>	0.359
	261.49	16226	1.025	0.048	1.027	0.048	1.025	0.048
	143.57	4968	<i>1.988</i>	0.335	<i>1.991</i>	0.335	<i>1.994</i>	0.335
neos-934278	3600.00	1184	1.000	0.991	1.000	0.993	1.000	0.993
	3600.00	265	1.000	1.014	1.000	1.011	1.000	1.003
	3600.00	263	1.000	1.000	1.000	1.000	1.000	0.989
	3600.00	391	1.000	1.014	1.000	1.014	1.000	0.963
	3600.00	521	1.000	1.002	1.000	0.997	1.000	0.998
neos18	24.17	1378	0.360	0.121	1.004	1.047	0.359	0.121
	21.26	1321	<i>1.154</i>	0.653	1.027	<i>1.199</i>	0.971	0.467
	23.36	1646	<i>1.227</i>	0.684	1.000	1.000	<i>1.229</i>	0.684
	19.21	996	0.808	0.443	1.003	1.000	0.805	0.443
	22.07	1049	0.989	0.925	0.997	1.000	0.951	0.795
ns1208400	2439.01	14168	0.485	0.271	0.146	0.062	0.484	0.271
	1985.63	7882	<i>1.390</i>	<i>1.450</i>	<i>1.673</i>	0.733	<i>1.392</i>	<i>1.450</i>
	1467.85	5026	0.367	0.355	0.416	0.283	0.367	0.355
	3600.00	5611	0.071	0.122	0.274	0.476	0.071	0.122
	2388.79	8711	0.050	0.068	0.650	0.464	0.051	0.068
ns1688347	55.09	451	0.942	0.975	<i>1.215</i>	<i>1.666</i>	0.940	0.975
	45.64	485	0.930	0.518	<i>1.058</i>	0.892	0.929	0.518
	106.90	1865	<i>1.530</i>	<i>1.438</i>	<i>1.160</i>	0.638	<i>1.330</i>	<i>1.366</i>
	139.57	1219	0.956	1.024	0.942	<i>1.088</i>	<i>1.205</i>	<i>1.089</i>
	55.82	745	0.858	0.527	0.724	0.608	0.862	0.527
ns1830653	132.81	6918	0.813	0.829	0.811	0.829	0.980	0.788
	123.49	5226	<i>1.250</i>	<i>1.054</i>	<i>1.251</i>	<i>1.054</i>	<i>1.515</i>	<i>1.580</i>
	161.13	9597	0.948	<i>1.090</i>	0.946	<i>1.090</i>	0.863	0.656
	143.05	7435	<i>1.065</i>	1.011	<i>1.069</i>	1.011	0.901	0.816
	146.20	9194	0.783	0.639	0.782	0.639	<i>1.160</i>	0.740

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Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
nsrand-ipx	422.05	50124	0.998	1.000	1.003	1.000	<i>1.297</i>	0.946
	643.65	86869	0.999	1.000	0.999	1.000	<i>1.274</i>	0.923
	568.28	56575	1.004	1.000	1.006	1.000	<i>1.058</i>	0.996
	582.50	61056	0.996	1.000	1.006	1.000	<i>2.291</i>	0.885
	367.03	38012	0.995	1.000	0.994	1.000	<i>1.147</i>	1.032
opt1217	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
p0033	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
p0201	0.55	5	0.981	1.000	0.987	1.000	0.987	1.000
	0.71	9	1.018	1.000	1.023	1.000	0.994	1.000
	1.59	5	1.015	1.000	1.015	1.000	1.004	1.000
	0.90	13	1.005	1.000	1.000	1.000	1.005	1.000
	0.91	59	0.984	1.000	0.984	1.000	0.984	1.000
p0282	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	3	1.007	1.000	1.000	1.000	1.007	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000
p0548	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000
p2756	2.46	5	1.006	1.000	1.012	1.000	1.000	1.000
	3.33	5	1.005	1.000	1.018	1.000	0.995	1.000
	2.16	3	0.994	1.000	0.987	1.000	0.994	1.000
	2.60	3	0.994	1.000	0.992	1.000	0.975	1.000
	1.22	2	1.036	1.000	1.027	1.000	1.041	1.000
protfold	3600.00	4783	1.000	0.685	1.000	1.008	1.000	0.685
	3600.00	8172	1.000	0.314	1.000	1.003	1.000	0.315
	3600.00	5838	1.000	0.478	1.000	1.004	1.000	0.480
	3600.00	7263	1.000	0.262	1.000	1.000	1.000	0.263
	3600.00	5620	1.000	0.348	1.000	0.844	1.000	0.345
pw-myciel4	3600.00	519843	1.000	0.696	0.656	0.587	1.000	0.901
	3600.00	443116	1.000	0.824	0.930	0.954	1.000	0.688
	3600.00	391642	1.000	0.830	1.000	0.968	1.000	0.969
	2920.77	395762	<i>1.232</i>	0.907	<i>1.232</i>	0.872	<i>1.232</i>	<i>1.067</i>

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	3600.00	405235	0.847	0.934	0.938	1.044	1.000	0.856
qnet1	4.52	33	1.004	1.000	1.009	1.000	1.007	1.000
	3.09	3	1.000	1.000	1.002	1.000	1.000	1.000
	3.94	29	1.002	1.000	1.004	1.000	1.000	1.000
	2.23	3	0.994	1.000	0.994	1.000	1.006	1.000
	3.69	34	0.998	1.000	0.998	1.000	0.989	1.000
qnet1_o	3.93	27	1.008	1.000	0.986	1.000	1.004	1.000
	3.35	24	1.009	1.000	1.005	1.000	1.002	1.000
	3.37	15	1.000	1.000	1.007	1.000	1.000	1.000
	1.66	2	1.008	1.000	1.004	1.000	0.992	1.000
	1.83	3	1.004	1.000	1.000	1.000	1.004	1.000
reblock67	222.59	49530	0.997	1.000	0.997	1.000	1.001	1.000
	161.89	40625	0.993	1.000	1.002	1.000	1.000	1.000
	194.41	49882	0.858	0.853	0.866	0.853	0.859	0.853
	199.06	50996	0.991	1.032	0.994	1.032	0.998	1.032
	239.84	57566	0.993	1.000	0.996	1.000	0.997	1.000
rmine6	971.86	111047	1.004	1.000	1.000	1.000	0.999	1.000
	883.48	89213	1.001	1.000	0.990	1.000	1.001	1.000
	775.32	91530	1.005	1.000	0.999	1.000	1.011	1.000
	740.58	85429	1.003	1.000	0.993	1.000	1.006	1.000
	771.48	76017	0.999	1.000	1.000	1.000	1.004	1.000
rococoC10-001000	601.83	46983	0.999	1.000	0.999	1.000	0.997	1.000
	833.40	75156	1.008	1.000	1.004	1.000	0.996	1.000
	517.62	37178	1.003	1.000	<i>1.090</i>	<i>1.105</i>	<i>1.089</i>	<i>1.105</i>
	892.04	51410	1.002	1.000	1.002	1.000	1.002	1.000
	1047.39	66016	1.000	1.000	1.001	1.000	1.001	1.000
seymour	3600.00	102645	1.000	0.996	1.000	0.999	1.000	0.997
	3600.00	120322	1.000	0.999	1.000	0.997	1.000	0.998
	3600.00	122337	1.000	1.006	1.000	1.004	1.000	1.007
	3600.00	107537	1.000	0.998	1.000	1.000	1.000	0.996
	3600.00	96726	1.000	1.007	1.000	1.001	1.000	0.999
sp98ir	57.90	3948	1.004	1.000	1.006	1.000	1.001	1.000
	65.87	4178	1.002	1.000	1.004	1.000	0.996	1.000
	67.64	4735	1.005	1.000	1.003	1.000	1.001	1.000
	72.68	4603	0.995	1.000	0.995	1.000	1.002	1.000
	70.05	4780	1.004	1.000	1.000	1.000	1.000	1.000
stein27	1.12	2749	1.009	1.000	1.024	1.000	1.024	1.000
	1.19	2699	1.009	1.000	0.991	1.000	1.000	1.000
	1.25	2889	0.991	1.000	0.982	1.000	0.996	1.000
	1.14	2715	0.977	<i>1.056</i>	0.963	1.000	0.991	<i>1.056</i>
	1.13	2911	0.981	0.972	0.991	1.000	1.023	0.972
stein45	12.80	40723	0.967	0.962	0.987	1.000	1.041	1.002
	12.94	39012	0.963	0.995	0.999	1.000	0.991	0.995

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Table 5: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	default		degeneracy + leaves		leaves + obj		all6criterion	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
	13.04	41930	1.010	0.985	0.998	1.000	1.015	0.985
	12.20	37543	1.038	1.015	0.998	1.000	1.044	1.015
	13.29	40503	0.984	1.006	0.985	1.000	1.003	1.006
tanglegram2	4.09	3	1.012	1.000	1.006	1.000	1.010	1.000
	3.85	3	1.000	1.000	1.006	1.000	0.996	1.000
	4.25	3	0.998	1.000	0.996	1.000	1.050	1.000
	4.11	3	0.994	1.000	0.990	1.000	1.004	1.000
	4.23	3	0.990	1.000	0.992	1.000	0.998	1.000

Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
10teams	3.01	1	0.990	1.000	0.825	1.000	0.995	1.000	0.988	1.000
	4.07	5	1.006	1.000	<i>1.266</i>	1.000	<i>1.162</i>	1.000	1.026	1.000
	25.62	956	1.012	1.000	0.668	0.159	<i>1.091</i>	<i>1.195</i>	0.441	0.118
	13.04	28	0.998	1.000	0.331	0.820	0.428	0.820	1.002	1.000
	4.40	5	1.004	1.000	<i>4.026</i>	<i>2.943</i>	<i>1.278</i>	1.000	1.007	1.000
30n20b8	189.53	63	<i>1.521</i>	<i>1.245</i>	<i>1.573</i>	<i>1.607</i>	<i>1.458</i>	<i>1.503</i>	1.000	1.000
	111.78	2	<i>2.089</i>	<i>1.873</i>	<i>1.975</i>	<i>1.676</i>	1.023	1.000	0.998	1.000
	87.35	4	1.001	1.000	0.993	1.000	0.999	1.000	1.001	1.000
	257.61	165	0.841	0.762	0.994	1.000	1.009	1.000	1.004	1.000
	381.26	182	0.982	0.926	<i>1.061</i>	0.858	1.005	1.000	0.999	1.000
acc-tight5	139.72	956	<i>1.284</i>	<i>1.562</i>	0.205	0.116	0.433	0.267	<i>1.560</i>	<i>1.788</i>
	110.82	1160	0.516	0.318	<i>1.515</i>	<i>1.136</i>	0.513	0.239	<i>1.140</i>	<i>1.150</i>
	49.06	174	<i>2.796</i>	<i>4.310</i>	<i>1.596</i>	<i>2.558</i>	0.623	0.442	<i>1.712</i>	<i>2.423</i>
	28.52	22	<i>2.037</i>	<i>1.828</i>	<i>2.899</i>	<i>4.975</i>	<i>1.400</i>	<i>1.434</i>	<i>5.993</i>	<i>11.180</i>
	30.00	17	1.019	1.000	0.936	<i>1.325</i>	<i>2.597</i>	<i>3.556</i>	1.012	<i>1.103</i>
air03	1.73	1	1.000	1.000	1.007	1.000	0.993	1.000	1.011	1.000
	1.72	1	1.015	1.000	1.000	1.000	1.011	1.000	0.996	1.000
	1.72	1	1.011	1.000	1.007	1.000	1.000	1.000	1.007	1.000
	1.75	1	1.000	1.000	0.993	1.000	0.993	1.000	1.004	1.000
	1.74	1	1.026	1.000	1.007	1.000	0.989	1.000	1.000	1.000
air04	49.60	110	1.009	1.000	1.008	1.000	1.008	1.000	1.008	1.000
	36.38	39	1.001	1.000	0.995	1.000	0.997	1.000	0.995	1.000
	53.17	118	0.999	1.000	0.988	1.000	0.998	1.000	1.002	1.000
	37.09	31	0.995	1.000	0.993	1.000	0.992	1.000	0.996	1.000
	48.66	122	0.996	1.000	0.994	1.000	1.002	1.000	0.999	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
air05	24.56	189	1.002	1.000	1.002	1.000	1.001	1.000	1.002	1.000
	26.64	239	1.000	1.000	0.998	1.000	0.998	1.000	1.009	1.000
	31.10	438	1.002	1.000	1.005	1.000	1.046	1.000	1.003	1.000
	27.57	283	1.000	1.000	1.000	1.000	0.999	1.000	0.998	1.000
	27.23	279	1.000	1.000	0.996	1.000	0.998	1.000	0.993	1.000
blend2	0.76	714	0.989	1.000	0.994	1.000	0.972	1.000	1.006	1.000
	1.05	973	1.015	1.000	0.980	1.000	1.005	1.000	1.005	1.000
	1.06	912	0.985	1.000	0.985	1.000	0.990	1.000	1.005	1.000
	0.66	543	1.018	1.000	0.994	1.000	0.994	1.000	1.012	1.000
	0.71	709	0.994	1.000	0.988	1.000	1.000	1.000	1.000	1.000
bley_xl1	163.94	1	0.996	1.000	1.004	1.000	1.005	1.000	1.004	1.000
	189.31	18	0.999	1.000	1.002	1.000	<i>1.052</i>	<i>1.314</i>	<i>1.107</i>	<i>1.458</i>
	162.64	2	0.984	1.000	0.999	1.000	1.000	1.000	1.003	1.000
	134.67	1	0.997	1.000	1.001	1.000	0.998	1.000	0.999	1.000
	136.43	1	1.003	1.000	1.001	1.000	1.003	1.000	1.003	1.000
bnatt350	18.90	6	0.897	1.000	<i>6.188</i>	<i>7.047</i>	<i>2.522</i>	<i>1.330</i>	<i>19.530</i>	<i>40.189</i>
	16.29	10	<i>1.098</i>	1.000	<i>27.910</i>	<i>46.845</i>	<i>2.398</i>	<i>1.309</i>	<i>13.634</i>	<i>15.082</i>
	18.02	6	0.834	1.000	<i>15.298</i>	<i>20.085</i>	<i>3.298</i>	<i>3.075</i>	<i>13.075</i>	<i>20.151</i>
	16.08	7	0.999	1.000	<i>12.361</i>	<i>12.720</i>	<i>1.444</i>	1.047	<i>17.894</i>	<i>26.383</i>
	43.21	112	0.732	0.623	<i>9.481</i>	<i>21.113</i>	<i>2.919</i>	<i>3.425</i>	<i>10.242</i>	<i>27.854</i>
cap6000	2.70	1830	1.008	1.000	1.000	1.000	1.003	1.000	1.005	1.000
	2.62	1837	0.992	1.000	1.017	1.000	0.978	1.000	1.003	1.000
	2.58	1959	1.025	1.000	1.028	1.000	1.011	1.000	1.014	1.000
	3.20	1924	0.976	1.000	0.983	1.000	0.974	1.000	0.993	1.000
	2.85	1762	0.982	1.000	0.992	1.000	0.992	1.000	0.984	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
cov1075	3560.96	1725170	1.001	1.000	1.001	1.000	1.011	0.827	1.001	1.000
	3600.00	1745291	1.000	1.000	1.000	1.006	1.000	1.009	1.000	1.003
	3600.00	1834965	1.000	0.998	1.000	1.001	1.000	0.823	1.000	0.990
	3600.00	1771419	1.000	1.000	1.000	0.999	1.000	1.007	1.000	1.000
	3600.00	1817274	1.000	0.999	1.000	0.999	1.000	0.657	1.000	0.999
csched010	3600.00	237694	1.000	0.997	1.000	0.997	1.000	0.996	1.000	0.997
	3600.00	203138	1.000	1.000	1.000	1.002	1.000	0.999	1.000	1.000
	2893.02	177527	0.998	1.000	1.001	1.000	1.000	1.000	0.999	1.000
	3600.00	238053	1.000	1.003	1.000	1.001	1.000	0.999	1.000	0.998
	3171.41	173932	0.999	1.000	0.999	1.000	0.998	1.000	1.000	1.000
eil33-2	69.62	583	1.004	1.000	1.001	1.000	0.996	1.000	1.003	1.000
	82.52	739	0.994	1.000	0.994	1.000	0.999	1.000	0.981	1.000
	83.95	847	1.012	1.000	1.013	1.000	1.016	1.000	1.010	1.000
	72.71	543	1.015	1.000	1.019	1.000	1.016	1.000	1.005	1.000
	69.08	583	1.016	1.000	1.016	1.000	1.015	1.000	1.017	1.000
eilB101	378.34	10582	0.995	1.000	0.990	1.000	1.012	1.000	1.000	1.000
	359.35	8427	1.009	1.000	1.001	1.000	1.017	1.000	1.011	1.000
	399.77	9358	1.003	1.000	0.999	1.000	0.999	1.000	1.005	1.000
	396.04	11465	1.006	1.000	0.995	1.000	1.012	1.000	0.997	1.000
	361.93	10006	1.009	1.000	1.011	1.000	1.013	1.000	1.006	1.000
enigma	0.50	650	1.000	0.997	1.033	<i>768.000</i>	<i>1.113</i>	<i>1.135</i>	1.000	1.033
	0.50	173	1.000	<i>1.681</i>	1.000	<i>1.905</i>	1.000	<i>1.495</i>	1.000	1.000
	0.50	63	1.000	<i>1.374</i>	1.000	<i>1.123</i>	1.027	<i>4.491</i>	1.000	1.000
	0.61	318	0.932	0.289	0.932	<i>1.122</i>	1.031	<i>1.218</i>	0.975	1.000
	0.53	196	1.013	<i>1.588</i>	0.980	0.405	0.980	<i>1.493</i>	1.000	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
enlight13	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
enlight14	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
fiber	1.02	2	0.995	1.000	0.980	1.000	1.000	1.000	1.000	1.000
	1.39	4	1.004	1.000	1.008	1.000	1.013	1.000	1.004	1.000
	1.76	4	0.982	1.000	0.996	1.000	0.978	1.000	0.993	1.000
	1.55	4	1.000	1.000	0.988	1.000	0.988	1.000	0.988	1.000
	1.00	3	0.995	1.000	1.010	1.000	1.005	1.000	1.005	1.000
flugpl	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
gt2	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
harp2	694.94	1491878	1.003	1.000	0.999	1.000	0.996	1.000	0.989	1.000
	1163.82	2857677	0.992	1.000	0.989	1.000	0.993	1.000	0.993	1.000
	333.99	595854	1.008	1.000	1.002	1.000	1.011	1.000	1.009	1.000
	934.82	2046181	1.006	1.000	0.999	1.000	1.001	1.000	1.003	1.000
	433.24	923780	0.998	1.000	0.985	1.000	0.991	1.000	0.996	1.000
iis-100-0-cov	625.29	103302	0.999	1.000	1.002	1.000	0.998	1.000	0.998	1.000
	544.56	92393	1.001	1.000	1.025	1.000	0.999	1.000	1.001	1.000
	520.20	81639	1.022	1.000	1.018	1.000	<i>1.069</i>	1.000	1.007	1.000
	507.53	84800	0.995	1.000	1.008	1.000	1.001	1.000	1.025	1.000
	542.59	92313	<i>1.055</i>	1.000	1.036	1.000	1.011	1.000	1.016	1.000
iis-bupa-cov	1917.51	157619	0.991	1.000	0.994	1.000	0.997	1.000	0.996	1.000
	1939.94	164079	1.010	1.000	1.019	1.000	1.014	1.000	1.020	1.000
	1878.21	156888	<i>1.053</i>	1.000	0.998	1.000	1.024	1.000	1.003	1.000
	1938.34	161969	1.002	1.000	1.022	1.000	1.026	1.000	1.002	1.000
	1802.15	158284	1.030	1.000	1.048	1.000	1.003	1.000	1.030	1.000
iis-pima-cov	292.21	4824	1.006	1.000	1.002	1.000	1.002	1.000	1.006	1.000
	434.93	12189	1.020	1.000	1.000	1.000	1.025	1.000	1.039	1.000
	246.99	4668	1.007	1.000	1.019	1.000	1.009	1.000	0.995	1.000
	285.55	6607	1.005	1.000	1.006	1.000	1.011	1.000	1.015	1.000
	558.43	17821	1.017	1.000	0.998	1.000	1.002	1.000	1.048	1.000
l152lav	5.47	23	0.994	1.000	0.998	1.000	1.009	1.000	1.000	1.000
	1.63	31	1.011	1.000	1.015	1.000	0.996	1.000	1.011	1.000
	2.93	50	0.992	1.000	0.987	1.000	1.000	1.000	1.003	1.000
	2.29	20	1.006	1.000	1.012	1.000	1.009	1.000	1.009	1.000
	3.00	52	1.012	1.000	1.010	1.000	1.015	1.000	1.012	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
lectsched-4-obj	20.11	95	0.957	<i>1.113</i>	<i>1.624</i>	<i>3.487</i>	1.008	<i>1.913</i>	<i>2.428</i>	<i>4.513</i>
	28.02	158	<i>1.120</i>	<i>1.093</i>	<i>1.242</i>	<i>2.430</i>	0.989	0.930	<i>2.457</i>	<i>2.988</i>
	24.11	565	0.645	0.415	<i>1.559</i>	<i>1.989</i>	<i>1.552</i>	<i>1.788</i>	<i>2.656</i>	<i>1.714</i>
	8.09	9	1.022	1.000	0.865	1.000	0.818	0.963	<i>9.364</i>	<i>11.716</i>
	20.57	114	<i>1.340</i>	<i>1.178</i>	<i>1.510</i>	<i>3.664</i>	<i>1.381</i>	<i>2.271</i>	<i>7.981</i>	<i>9.061</i>
lseu	0.77	268	1.011	1.000	0.977	1.000	1.000	1.000	0.994	1.000
	0.50	4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	205	1.000	1.000	1.020	1.000	1.000	1.000	1.000	1.000
	0.50	91	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.51	191	0.993	1.000	1.007	1.000	0.993	1.000	1.020	1.000
m100n500k4r1	3600.00	2426435	1.000	1.032	1.000	0.997	1.000	0.957	1.000	0.883
	3600.00	2358830	1.000	0.997	1.000	0.993	1.000	<i>1.414</i>	1.000	0.897
	3600.00	2313256	1.000	1.028	1.000	0.982	1.000	1.039	1.000	0.982
	3600.00	2163125	1.000	1.040	1.000	0.997	1.000	<i>1.441</i>	1.000	0.950
	3600.00	1871050	1.000	<i>1.054</i>	1.000	0.975	1.000	<i>1.115</i>	1.000	1.032
macrophage	125.68	5163	1.001	1.000	0.999	1.000	1.002	1.000	1.001	1.000
	157.07	7241	1.007	1.000	1.007	1.000	1.007	1.000	1.005	1.000
	209.04	9131	1.010	1.000	0.998	1.000	1.003	1.000	1.006	1.000
	162.46	7927	1.039	1.000	1.002	1.000	1.013	1.000	1.008	1.000
	121.23	5239	0.997	1.000	1.015	1.000	0.998	1.000	1.014	1.000
manna81	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
markshare1	3600.00	17773362	1.000	<i>1.150</i>	1.000	0.990	1.000	1.038	1.000	0.655
	3600.00	17405834	1.000	<i>1.184</i>	1.000	0.998	1.000	<i>1.126</i>	1.000	1.000
	3600.00	17945211	1.000	<i>1.149</i>	1.000	1.001	1.000	0.954	1.000	0.482
	3600.00	18348094	1.000	<i>1.131</i>	1.000	1.003	1.000	0.980	1.000	0.853
	3600.00	17151823	1.000	<i>1.130</i>	1.000	0.997	1.000	<i>1.050</i>	1.000	0.889
markshare2	3600.00	3433363	1.000	<i>1.178</i>	1.000	1.003	1.000	<i>1.352</i>	1.000	<i>1.064</i>
	3600.00	3929356	1.000	0.901	1.000	1.003	1.000	<i>1.127</i>	1.000	0.877
	3600.00	3675025	1.000	1.036	1.000	1.000	1.000	0.975	1.000	1.004
	3600.00	4532415	1.000	0.819	1.000	0.999	1.000	1.032	1.000	0.789
	3600.00	4267105	1.000	0.860	1.000	1.009	1.000	0.887	1.000	<i>1.101</i>
mcsched	285.70	13689	1.000	1.000	0.998	1.000	1.004	1.000	1.000	1.000
	271.59	11373	0.998	1.000	1.015	1.000	1.022	1.000	0.999	1.000
	233.00	10059	1.014	1.000	1.036	1.000	1.006	1.000	1.001	1.000
	285.38	12496	1.011	1.000	1.003	1.000	0.998	1.000	0.996	1.000
	272.13	10373	0.997	1.000	1.009	1.000	1.027	1.000	1.016	1.000
mine-166-5	58.40	1569	0.997	1.000	0.998	1.000	0.997	1.000	0.999	1.000
	57.21	1191	1.007	1.000	1.003	1.000	0.998	1.000	1.005	1.000
	46.49	2244	<i>1.064</i>	1.000	1.010	1.000	1.007	1.000	0.999	1.000
	65.30	139	0.991	1.000	1.003	1.000	1.043	1.000	1.003	1.000
	42.28	2863	<i>1.061</i>	1.000	1.002	1.000	1.021	1.000	1.019	1.000
mine-90-10	276.51	47643	1.001	1.000	0.997	1.000	0.999	1.000	0.997	1.000
	125.11	22195	1.002	1.000	1.001	1.000	1.013	1.000	1.018	1.000
	173.38	25979	1.042	1.000	1.001	1.000	1.010	1.000	1.020	1.000
	502.57	87496	0.998	1.000	0.995	1.000	1.005	1.000	0.997	1.000
	237.48	32520	1.002	1.000	<i>1.054</i>	1.000	0.992	1.000	0.999	1.000

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Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
misc03	1.40	398	0.988	1.000	0.992	1.000	0.983	1.000	0.988	1.000
	0.71	15	1.023	1.000	1.018	1.000	1.006	1.000	1.000	1.000
	0.73	19	1.000	1.000	0.983	1.000	0.988	1.000	0.977	1.000
	0.98	111	1.025	1.000	1.015	1.000	0.990	1.000	1.020	1.000
	0.64	15	1.018	1.000	1.000	1.000	1.000	1.000	1.018	1.000
misc07	38.28	28289	0.997	1.000	0.990	1.000	0.982	1.000	0.995	1.000
	36.49	29782	1.007	1.000	1.006	1.000	1.006	1.000	1.007	1.000
	21.45	17632	1.003	1.000	1.010	1.000	1.004	1.000	1.003	1.000
	45.80	38975	1.014	1.000	1.013	1.000	1.004	1.000	1.007	1.000
	30.56	29476	1.010	1.000	1.014	1.000	1.009	1.000	1.009	1.000
mitre	14.57	1	1.006	1.000	0.757	1.000	0.984	1.000	0.988	1.000
	15.57	1	0.992	1.000	0.717	1.000	0.993	1.000	0.999	1.000
	15.52	1	1.005	1.000	0.718	1.000	1.005	1.000	1.001	1.000
	15.17	1	0.988	1.000	0.746	1.000	0.994	1.000	1.001	1.000
	13.39	1	1.037	1.000	0.994	1.000	1.027	1.000	1.028	1.000
mod008	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.53	2	1.000	1.000	0.987	1.000	1.013	1.000	1.007	1.000
	0.54	2	0.987	1.000	0.981	1.000	0.987	1.000	0.994	1.000
	0.51	1	1.000	1.000	1.000	1.000	1.007	1.000	1.013	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
mod010	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.53	2	0.993	1.000	0.980	1.000	1.000	1.000	0.987	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
mzzv11	332.03	2022	0.995	1.000	0.995	1.000	0.998	1.000	0.996	1.000
	229.82	959	1.005	1.000	0.999	1.000	0.991	1.000	0.999	1.000
	311.22	1421	0.987	1.000	1.000	1.000	0.996	1.000	0.988	1.000
	322.67	1579	1.009	1.000	1.014	1.000	1.009	1.000	0.998	1.000
	186.23	627	1.002	1.000	0.999	1.000	1.000	1.000	0.997	1.000
mzzv42z	151.11	265	0.994	1.000	1.003	1.000	1.001	1.000	1.001	1.000
	131.14	125	0.994	1.000	0.995	1.000	0.998	1.000	0.995	1.000
	198.89	200	1.000	1.000	0.996	1.000	0.995	1.000	0.999	1.000
	214.35	456	0.997	1.000	1.005	1.000	0.998	1.000	0.990	1.000
	167.53	300	1.005	1.000	0.998	1.000	1.000	1.000	1.001	1.000
neos-1109824	37.38	1796	0.998	1.000	0.997	1.000	0.996	1.000	0.997	1.000
	46.57	3438	1.012	1.000	1.006	1.000	1.008	1.000	1.035	1.000
	34.97	1913	1.013	1.000	1.009	1.000	1.021	1.000	1.022	1.000
	77.32	8290	1.043	1.000	1.005	1.000	<i>1.055</i>	1.000	1.036	1.000
	39.22	2247	1.008	1.000	1.010	1.000	1.010	1.000	1.038	1.000
neos-1337307	3600.00	306352	1.000	0.991	1.000	0.993	1.000	0.994	1.000	0.993
	3600.00	269284	1.000	0.998	1.000	0.979	1.000	1.002	1.000	0.952
	3600.00	349832	1.000	0.970	1.000	0.996	1.000	0.996	1.000	0.991
	3600.00	301363	1.000	0.989	1.000	0.978	1.000	0.932	1.000	1.006
	3600.00	373217	1.000	0.995	1.000	0.991	1.000	0.983	1.000	0.986
neos-1601936	2033.50	1453	0.999	1.000	0.994	1.000	0.999	1.000	0.996	1.000
	3600.00	2861	1.000	0.996	1.000	1.001	1.000	1.000	1.000	1.000
	1338.93	2661	1.013	1.000	1.006	1.000	1.008	1.000	1.009	1.000
	3600.00	6917	1.000	1.004	1.000	1.000	1.000	0.990	1.000	0.999
	3600.00	6139	1.000	1.000	1.000	0.977	1.000	1.000	1.000	1.010

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Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
neos-686190	83.27	4906	0.996	1.000	1.002	1.000	0.995	1.000	0.996	1.000
	86.55	6047	1.000	1.000	1.013	1.000	0.997	1.000	1.000	1.000
	115.34	9156	0.995	1.000	0.994	1.000	1.021	1.000	1.006	1.000
	117.19	9998	0.995	1.000	1.006	1.000	0.992	1.000	0.996	1.000
	120.84	9806	1.008	1.000	0.998	1.000	1.003	1.000	1.007	1.000
neos-849702	207.98	1169	<i>1.979</i>	<i>8.256</i>	<i>6.088</i>	<i>54.068</i>	<i>2.833</i>	<i>25.153</i>	<i>4.876</i>	<i>14.426</i>
	1025.85	6328	0.139	0.049	0.772	<i>1.387</i>	0.158	0.594	0.999	1.000
	1001.35	10499	0.904	0.400	0.181	0.099	0.686	<i>5.053</i>	1.016	1.000
	267.07	683	<i>2.864</i>	<i>2.388</i>	<i>2.815</i>	<i>9.508</i>	0.763	<i>13.476</i>	<i>5.812</i>	<i>84.398</i>
	285.44	1596	<i>1.679</i>	<i>1.538</i>	<i>1.067</i>	0.353	0.470	<i>4.297</i>	<i>5.308</i>	<i>35.870</i>
neos-934278	3600.00	1175	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.006
	3600.00	267	1.000	0.995	1.000	1.008	1.000	1.000	1.000	0.995
	3600.00	263	1.000	1.000	1.000	1.008	1.000	0.983	1.000	1.008
	3600.00	401	1.000	0.992	1.000	0.994	1.000	0.992	1.000	0.994
	3600.00	522	1.000	0.998	1.000	0.998	1.000	1.000	1.000	0.997
neos18	8.13	79	<i>1.234</i>	<i>1.078</i>	<i>2.113</i>	<i>3.598</i>	<i>1.604</i>	<i>2.369</i>	<i>2.852</i>	<i>4.073</i>
	24.87	828	1.043	<i>1.054</i>	<i>1.347</i>	<i>1.815</i>	<i>1.232</i>	<i>1.531</i>	0.999	1.028
	28.94	1095	<i>1.089</i>	1.000	0.883	0.965	0.680	0.362	0.689	0.585
	15.42	386	1.001	0.965	<i>1.107</i>	<i>1.091</i>	<i>1.161</i>	0.872	<i>2.091</i>	<i>2.175</i>
	21.77	963	0.961	0.949	<i>1.249</i>	<i>1.147</i>	0.928	0.710	<i>1.281</i>	0.871
ns1208400	938.01	3025	0.912	0.753	0.543	0.314	0.763	0.692	1.017	1.032
	2737.49	11477	0.667	0.375	0.269	0.100	0.220	0.081	1.005	1.000
	532.73	1719	<i>1.828</i>	<i>1.341</i>	0.710	0.800	<i>1.579</i>	0.825	<i>2.439</i>	<i>2.687</i>
	253.07	599	<i>2.316</i>	<i>2.724</i>	<i>1.530</i>	<i>1.409</i>	<i>1.318</i>	0.720	<i>2.093</i>	<i>2.482</i>
	1316.58	2660	<i>1.221</i>	<i>1.112</i>	<i>1.259</i>	<i>2.671</i>	0.330	0.303	1.015	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
ns1688347	51.67	437	<i>1.239</i>	<i>1.255</i>	1.025	<i>1.220</i>	<i>1.103</i>	0.719	0.998	1.000
	42.42	203	<i>1.423</i>	<i>2.165</i>	<i>1.332</i>	<i>2.370</i>	<i>1.406</i>	<i>2.670</i>	<i>1.886</i>	<i>4.353</i>
	161.82	3095	<i>1.050</i>	0.752	0.833	0.552	<i>1.111</i>	0.556	1.003	1.000
	133.50	1251	0.878	0.597	0.964	0.638	1.049	<i>1.245</i>	1.008	1.000
	51.48	399	0.948	0.890	<i>1.378</i>	<i>2.481</i>	0.953	<i>1.156</i>	<i>1.274</i>	<i>1.691</i>
ns1830653	133.08	6918	0.993	1.000	0.998	1.000	0.994	1.000	0.995	1.000
	123.87	5226	0.999	1.000	0.997	1.000	<i>1.061</i>	1.000	1.007	1.000
	161.00	9597	1.004	1.000	1.001	1.000	1.001	1.000	1.007	1.000
	143.21	7435	<i>1.054</i>	1.000	1.005	1.000	0.995	1.000	1.002	1.000
	146.08	9194	1.000	1.000	1.004	1.000	1.007	1.000	1.002	1.000
nsrand-ipx	419.85	50124	1.006	1.000	1.005	1.000	1.007	1.000	1.001	1.000
	638.54	86869	1.002	1.000	1.005	1.000	0.999	1.000	1.005	1.000
	569.66	56575	0.994	1.000	1.003	1.000	1.005	1.000	1.004	1.000
	582.34	61056	1.004	1.000	1.001	1.000	1.000	1.000	1.002	1.000
	363.56	38012	1.007	1.000	1.002	1.000	1.002	1.000	1.000	1.000
opt1217	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p0033	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
p0201	0.54	5	1.006	1.000	1.013	1.000	1.019	1.000	1.000	1.000
	0.74	9	0.989	1.000	1.000	1.000	0.983	1.000	1.011	1.000
	1.64	5	1.000	1.000	1.004	1.000	0.985	1.000	0.996	1.000
	0.90	13	1.000	1.000	1.000	1.000	1.000	1.000	1.011	1.000
	0.89	59	1.005	1.000	1.005	1.000	1.011	1.000	1.016	1.000
p0282	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	3	1.000	1.000	1.000	1.000	1.007	1.000	1.000	1.000
	0.50	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p0548	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	0.50	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
p2756	2.51	5	0.991	1.000	0.989	1.000	1.000	1.000	0.994	1.000
	3.33	5	1.009	1.000	1.005	1.000	1.009	1.000	1.007	1.000
	2.13	3	0.994	1.000	0.990	1.000	0.987	1.000	1.006	1.000
	2.54	3	1.000	1.000	1.008	1.000	1.006	1.000	1.014	1.000
	1.28	2	1.000	1.000	0.996	1.000	1.004	1.000	1.009	1.000
protfold	3600.00	3244	1.000	0.823	1.000	0.632	1.000	<i>2.305</i>	1.000	<i>1.328</i>
	3600.00	2504	1.000	0.715	1.000	0.988	1.000	<i>2.045</i>	1.000	0.950
	3600.00	2755	1.000	0.858	1.000	<i>1.160</i>	1.000	<i>1.907</i>	1.000	0.733
	3600.00	1831	1.000	<i>1.278</i>	1.000	<i>1.551</i>	1.000	<i>2.081</i>	1.000	<i>1.256</i>
	3600.00	1867	1.000	0.814	1.000	<i>1.325</i>	1.000	<i>1.584</i>	1.000	0.831

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Table 6: Detailed computational results on MMM-IP with five random seeds. Relative changes by at least 5% are highlighted in bold and blue (**improvement**) or italic and red (*deterioration*).

Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
pw-myciel4	3600.00	361131	1.000	<i>1.253</i>	0.383	0.439	1.000	<i>1.320</i>	1.000	<i>1.077</i>
	3600.00	365865	1.000	1.039	1.000	0.895	1.000	<i>1.253</i>	1.000	<i>1.054</i>
	3600.00	323450	1.000	<i>1.199</i>	1.000	<i>1.102</i>	1.000	<i>1.294</i>	1.000	<i>1.161</i>
	3600.00	358151	1.000	1.020	1.000	0.856	1.000	<i>1.395</i>	0.925	<i>1.097</i>
	3054.26	378549	<i>1.179</i>	0.843	<i>1.179</i>	<i>1.128</i>	<i>1.179</i>	1.019	<i>1.179</i>	0.893
qnet1	4.54	33	1.002	1.000	0.998	1.000	1.002	1.000	1.005	1.000
	3.12	3	0.995	1.000	1.007	1.000	1.002	1.000	0.993	1.000
	3.92	29	1.002	1.000	0.996	1.000	0.996	1.000	1.006	1.000
	2.26	3	0.991	1.000	0.991	1.000	0.994	1.000	0.991	1.000
	3.71	34	0.994	1.000	1.002	1.000	0.996	1.000	0.987	1.000
qnet1_o	3.87	27	1.012	1.000	1.002	1.000	1.010	1.000	1.008	1.000
	3.38	24	1.000	1.000	0.995	1.000	0.995	1.000	1.002	1.000
	3.39	15	0.995	1.000	1.000	1.000	0.993	1.000	1.000	1.000
	1.67	2	1.000	1.000	1.000	1.000	0.993	1.000	1.004	1.000
	1.84	3	1.000	1.000	1.007	1.000	1.000	1.000	1.007	1.000
reblock67	223.13	49530	0.998	1.000	0.995	1.000	0.995	1.000	0.989	1.000
	161.91	40625	1.001	1.000	1.004	1.000	1.006	1.000	1.019	1.000
	194.68	49882	1.002	1.000	1.006	1.000	0.999	1.000	1.032	1.000
	200.17	50996	1.006	1.000	1.001	1.000	0.992	1.000	0.995	1.000
	239.14	57566	1.017	1.000	0.999	1.000	1.002	1.000	0.999	1.000
rmine6	971.59	111047	0.997	1.000	1.002	1.000	0.999	1.000	1.003	1.000
	882.29	89213	0.999	1.000	1.040	1.000	1.013	1.000	1.026	1.000
	776.69	91530	0.992	1.000	1.000	1.000	1.004	1.000	1.021	1.000
	742.25	85429	1.010	1.000	1.001	1.000	1.005	1.000	1.000	1.000
	773.39	76017	0.995	1.000	1.002	1.000	1.013	1.000	0.995	1.000

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Instance	degeneracy		variablebounds		conflicts		infervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
rococoC10-001000	603.64	46983	0.995	1.000	0.997	1.000	0.994	1.000	0.995	1.000
	836.01	75156	0.999	1.000	0.998	1.000	0.998	1.000	1.007	1.000
	516.72	37178	<i>1.052</i>	1.000	1.006	1.000	1.003	1.000	1.006	1.000
	893.05	51410	0.999	1.000	1.006	1.000	1.004	1.000	1.001	1.000
	1048.40	66016	1.004	1.000	1.010	1.000	1.008	1.000	1.003	1.000
seymour	3600.00	102192	1.000	1.003	1.000	1.002	1.000	1.007	1.000	1.000
	3600.00	120186	1.000	1.002	1.000	0.996	1.000	1.000	1.000	1.000
	3600.00	123015	1.000	1.003	1.000	0.997	1.000	0.997	1.000	0.990
	3600.00	108085	1.000	1.001	1.000	0.996	1.000	0.998	1.000	0.995
	3600.00	97046	1.000	1.001	1.000	0.994	1.000	0.999	1.000	1.001
sp98ir	58.06	3948	0.999	1.000	0.997	1.000	1.000	1.000	0.999	1.000
	65.95	4178	1.039	1.000	1.003	1.000	1.012	1.000	1.006	1.000
	67.93	4735	1.000	1.000	1.029	1.000	1.020	1.000	1.014	1.000
	72.47	4603	1.003	1.000	1.005	1.000	1.003	1.000	1.011	1.000
	69.87	4780	<i>1.063</i>	1.000	0.998	1.000	1.001	1.000	1.013	1.000
stein27	1.17	2749	0.972	1.000	1.014	1.000	1.023	1.000	0.995	1.000
	1.23	2699	1.000	1.000	0.969	1.000	0.996	1.000	0.978	1.000
	1.19	2889	0.995	1.000	1.018	1.000	1.014	1.000	1.023	1.000
	1.13	2873	0.953	1.000	0.958	1.000	0.962	0.947	1.014	1.000
	1.08	2827	1.019	1.000	1.010	1.000	1.014	1.029	0.990	1.000
stein45	12.59	39175	0.994	1.000	0.989	1.000	0.996	1.039	0.997	1.000
	12.49	38805	1.004	1.000	1.005	1.000	1.024	1.005	1.003	1.000
	13.04	41279	1.005	1.000	1.024	1.000	0.998	1.016	1.004	1.000
	12.49	38104	1.006	1.000	1.004	1.000	0.980	0.985	1.004	1.000
	13.02	40755	1.008	1.000	0.997	1.000	1.009	0.994	0.994	1.000

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Instance	degeneracy		variablebounds		conflicts		intervals		primsols	
	time	nodes	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q	time _Q	nodes _Q
tanglegram2	4.11	3	1.002	1.000	1.006	1.000	0.990	1.000	1.000	1.000
	3.90	3	1.022	1.000	0.994	1.000	1.014	1.000	1.016	1.000
	4.20	3	1.012	1.000	1.008	1.000	1.015	1.000	1.008	1.000
	4.12	3	1.020	1.000	1.008	1.000	1.008	1.000	1.016	1.000
	4.20	3	1.000	1.000	1.000	1.000	1.038	1.000	1.000	1.000